How to implement QMRA?
to Estimate Baseline and Hazardous Event Risks
with Management End Uses In Mind

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Acknowledgements

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8.1 INTRODUCTION

The goal of this chapter is to illustrate how Quantitative Microbial Risk Assessment (QMRA) can be undertaken in practice utilising case studies from the MicroRisk project. It outlines the data analysis strategies and describes the simulation methods using illustrative input and output data collected on selected Catchment-to-Tap Systems (CTSs). It is designed to show:

- What system-level QMRA analyses require;
- How sub-model component (e.g. models describing each barrier) vary depending on such factors as data quality, data selection, source water quality and treatment system design;
- How widely the risk magnitudes estimated vary depending on the issue being addressed, the level of analysis sophistication (Tier), the pathogens modelled, and CTS structure;
- How the data output varies with aim of a simulation (e.g. estimation of ‘Baseline’ or ‘Hazardous Event’ effects); and
- How risk estimates might be used to support water management activities.

It is proposed that for each CTS/pathogen combination a full risk analysis involve 4 stages.

1. Baseline QMRA
Firstly risks to consumers from their water supply would be estimated for ‘nominal’ or Baseline conditions; that is the predominant operating conditions under which a CTS is understood to supply water to consumers. By virtue of their predominance, Baseline conditions should have the most comprehensive associated sets of system performance and operations information. Risks associated with Baseline conditions would by definition be the minimum achievable and hence the first to be assessed for acceptability.

2. Sensitivity Analysis
The second step is to undertake ‘Sensitivity Analysis’ on Baseline risk probability. Each barrier or stage is set in turn to its worst reasonable value and the simulation model is rerun. The process forces the water manager to critically consider vulnerable points (Control Points) within the supply train and estimate a worst case situation. The Factor Sensitivity (FS) values calculated by dividing each extreme (perturbed) Baseline simulate risk value by the normal Baseline risk, which serves to identify where Hazardous Events might lead to elevated risks.

3. Hazardous Events QMRA
Next the risks arising from specific ‘Hazardous Events’ [Nadebaum et al. 2004] are modelled. Hazardous Event conditions are assumed to apply when there is a perturbation from Baseline conditions which increases the infection risk to consumers. The increase in risk is estimated by simulating Baseline and Hazardous Event conditions and combining the risks in proportion to the time the CTS is in one or other state to estimate a Baseline+Hazardous Event risk. Sensitivity Analysis issues and outputs act as guides to scenario construction. Though the risk increase from several concurrent Hazardous Events can be simulated, a meaningful total Baseline+Hazardous Events risk cannot be calculated in practice because of the conceptual uncertainties. Currently there is little data suited to QMRA on the magnitude, duration and diverse attributes of many common Hazardous Events. And by definition there is almost no useful data on rare, high impact Hazardous Events.

4. Use of QMRA results in risk management
Finally the Baseline and Hazardous Event risk estimates and models are used to inform water supply management. The Risk probability estimates (probability infection.person\(^{-1}\).y\(^{-1}\)) are used in two ways. Baseline and Hazardous Event risk estimates provide relative measures of
risk which can be used to judge whether an alternative scenario (new plant, altered source water etc.) leads to a marked increase in risk compared to that already existing. Additionally where data is considered reliable enough, risk estimates may be treated as providing absolute measures of risk which can be compared to predetermined Tolerable Risk limits to determine whether a operating conditions under a given water supply scenario provides 'safe’ or whether specific processes are within acceptable ‘Critical Limits’.

This chapter concludes with a discussion outlining the strengths and limitations of the actual QMRA input and output data and suggests how the QMRA approach presented here can support and be integrated in practice with Water Safety Planning.

This chapter is structured as follows:
- An outline of how microbial data has been used for QMRA analysis and considerations informing these analyses;
- An illustrative worked example of one CTS (CTS 8) detailing the calculation of Baseline risks posed by one index pathogen, Campylobacter;
- Extension of the basic risk estimation approach to Sensitivity Analysis, the estimation of the risk arising from Hazardous Events, management including the estimation of Critical Limits and supplementation of Baseline risks with those resulting from Hazardous Events in the Distribution system;
- Illustration of the diversity of risks estimates encountered when a range of CTSs and pathogens are analysed concurrently; and
- A discussion of the uses and limitations of QMRA, its benefits and strengths.

8.2 METHODS AND ISSUES FOR A WATER MANAGER’S CONSIDERATION

8.2.1 Simulation of Risk within the Context of Water Safety Planning

QMRA application is a moderately complex procedure. Consequently the Water Manager should be clear about why they are doing QMRA, what information they intend to obtain from the process by way of better understanding and managing risks in their CTS and how far they intend to take the process. They should also be prepared to stop the process early as a contingency. This could occur because a simple analysis is all that is required as when absolute risks are either trivial or very severe and the answer to the issue being considered is evident. At the other extreme a critical data gap may exist such as a lack of credible source water data on the pathogen of interest. In this case new field measurements of water quality or treatment processes may be necessary before a useful outcome can be provided.

8.2.2 Decision Making and QMRA in Practice

Science and mathematics underpin pathogen behaviour concepts, analytical methods, and the probability theory underlying QMRA and modelling technology. This association tacitly suggests that water treatment Decision-Making (e.g. process management, disaster response) based on QMRA is also ‘scientific’ and ‘objective’. This is however a misapprehension which water managers must avoid if they are to use QMRA appropriately.
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The application of science to environmental policy and decisions has numerous limitations and complications which have become evident with increased understanding of how science works in practice [e.g. see Giampetro et al. 2006]. This does not imply science has no place in management decisions but rather its roles and relationship need clear definition.

Dowie [2005] outlines the problem as it applies to ‘Evidence Based Medicine’ of how to translate probabilistic scientific knowledge into risk decisions which minimise human health risks. He proposes a range of solutions based “Decision Making” concepts arising consideration of how Bayesian Statistics work (term proposed by the author in Bayesian Decision Analysis). This same general objective, of wishing to apply sound statistics (on water treatment process effectiveness) to decision making (e.g. need to upgrade treatment) is faced by water supply managers.

From consideration of Dowie’s [2005] arguments the following is proposed, by analogy, regarding pathogen risk assessment and management and where QMRA might fit in:

- Management decisions based on traditional water supply concepts (e.g. no coliforms = safe water) and the newer qualitative risk assessment approach are in actuality based on risk probability estimation. But the probability estimation process is tacit and is based on intuition informed by expert knowledge of waterborne pathogens etc. rather than strict statistical approaches.
- Experts can consider a range of diverse information of waterborne pathogen risks and through experience integrate and reduce risks. But they are not good at combining multiple numerical probabilities and estimating aggregate risks intuitively.
- To improve ‘Decision Making’ aggregate probabilities can be better estimated by substituting intuited probabilities where possible with ones calculated systematically using probability theory.

In summary QMRA appears to have great potential as an adjunct to water management decision making and qualitative risk assessment not only intuitively but from theory being currently developed in allied disciplines.

8.2.3 Risk Assessment Tiers

A concept often encountered in different risk assessment fields in that of Tiers [e.g. KarDouzas and Capri 2004; CMPHU; 2005; Hendley et al. 1998; Hart et al. 2005]. Practically Tiers have two common roles. Firstly they identify to a reviewer the general extent to which a risk analysis has been undertaken and hence its general strengths and limitations in support of decisions and whether it is sufficient for the desired decision support role. Secondly as outlined in Chapter 7, they provide a logical sequence whereby the complexity of a risk assessment exercise may be varied according to what information is needed. This sequence is summarised in Figure 7.4.

With this in mind Dowie’s [2005] recommendations were reconsidered with a view to identifying a possible basis for a QMRA Tier classification. Four ways were identified in which intuition dominated CTS risk assessments are replaced by systematic and statistical data treatment as proposed within QMRA:
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1. Replacement of the zero risk concept (no indicators present) with numerical probability estimates;
2. Replacement of end of system risk assessment (e.g. coliform testing on finished water) with assessment of the contribution of all water supply stages (i.e. analysis of barrier by barrier removal);
3. Recognition that water quality, barrier process effectiveness and risk probability data are better described by probability density functions (PDF) than point values; and
4. Recognition that the future behaviour of a specific CTS is being predicted from historical data sets whose applicability to the system of interest varies.

As each of these enhancements represents a different way in which BDA principles can be applied to CTS risk assessment it is proposed that the extent to which these enhancements are implemented be the basis for a series of QMRA Tiers, specifically that:

- Tier 1 be equivalent to enhancements 1 and 2
- Tier 2 be equivalent to enhancements 1, 2 and 3
- Tier 3 be equivalent to enhancements 1, 2, 3 and 4.

In this scheme the Tiers roughly equate to:
- Modelling of pathogen reduction by barriers using point values also known as screening level risk assessment (Tier 1);
- Monte Carlo style modelling of source water concentration and barrier effects as simple distributions based on minimal assumptions of PDF attributes largely using data derived from general literature (Tier 2); and
- Monte Carlo style barrier modelling using CTS specific data to estimate PDFs, variability and uncertainty (Tier 3).

The practicality and use of this Tier assignment classification model is illustrated in Section 8.3. The primary aim is not to establish a specific Tier classification scheme but to demonstrate how the Tier concept could work, trial it on a real set of data and illustrate the different possible QMRA outputs and model assumptions which may be developed for even a single CTS/pathogen risk assessment.

8.2.4 An Illustrative CTS and Index Pathogen

The system selected for illustrative purposes was CTS 8. This system was selected as:
- This catchment-to-consumer system is essentially a simple linear one with a single source dominant water and homogenous water treatment plant wherein all water receives exactly the same type and degree of treatment;
- A large body of historical pathogen and indicator information was available for this CTS and additional data was collected on most barriers during the course of the MicroRisk project; and
- Good ancillary data was available including catchment hydrology information, and treatment plant SCADA data.

The basic structure of CTS 8 is shown in Figure Error! No text of specified style in document.-1. The four principle barriers modelled (a reservoir, a flocculation/coagulation step, a particulate filter and disinfection system) were commonly encountered among the other MicroRisk CTSs. Also the conceptual barrier configuration of CTS 6 was very similar (River source > reservoir > flocculation > particle filter > disinfection > storage >
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distribution). The modelling process necessarily involved some simplifications of the system i.e. omission of pre-chlorination and sludge feedback, but this was seen as reasonable as the former process was not used during the study period and the quantity of water recycled was small compared to the total volume.

*Campylobacter* was selected as the illustrative index pathogen as available data was extensive and of a high quality. Measurements of full-scale removal of indicators and surrogates of this pathogen by several system barriers were also available.

![Figure](Error! No text of specified style in document.)

**Figure** _Error! No text of specified style in document._-1. Process diagram of CTS 8

### 8.2.5 The Logistics of Barrier Modelling

The challenge posed initially to the MicroRisk team of modeling 12 CTSs, each with several barriers, six index pathogens and a range of Hazardous Events and other factors influencing water quality, brought home the need for strategies for implementing QMRA efficiently and addressing logistics issues such as:

1. The range of pathogens to be assessed;
2. Data management (i.e. review, collation, archiving selection, analysis, model modification and quality assurance);
3. Water managers having responsibility for tens or many more CTSs and the need for a prioritization system;
4. Baseline water quality variability;
5. Hazardous Events of variable type, duration, impact and magnitude;
6. Hazardous Events of extreme impact potential for which there is little or no data;
7. The task of comparing different risk reduction options;
8. Data gap filling and model revision in light of initial model development; and
9. The need for systematic data management to account for the above issues.

Three strategies were identified to help address these issues and the need for ‘living’ risk assessment systems. Firstly application of the Tier concept (see above and Chapter 7) provided a scheme for only undertaking as much risk assessment as decision making...
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warranted. It also allowed the quality of barrier models to be assessed and data gaps and limitations to be identified.

Secondly we adapted the concept of Hazardous Events [Nadebaum et al. 2004] to define their converse – Baseline or ‘nominal’ water supply conditions when there are no notable perturbations in pathogen concentrations or their removal. This concept outlined by Teunis et al. [in press] provides a natural starting point for risk modelling and was incorporated into the Metamodel Design (Section 8.2.7). Data sampling strategies developed with Hazardous Events in mind could be adapted to allow modelling of other aspects of water quality and treatment variability such as that occurring between different seasons. Simulation of Hazardous Events also provided a means for exploring potential high risk situations identified via Sensitivity Analysis and the conceptual basis for quantitative setting of Critical Limits. The relationship between barriers simulation and Baselines, Sensitivity Analysis, Hazardous Events and Critical Limits are summarized in Figure Error! No text of specified style in document.-2. Figure Error! No text of specified style in document.-2 expands on key parts of the general assessment framework (Figure 7-1) to show how the latter has been applied in practice.

The third strategy pertained to programming philosophy. Creating simple barrier simulation models with or without Monte Carlo models is straightforward. It can be undertaken with a range of software and even with Microsoft Excel spreadsheets enhanced with add-ins such as Crystal-Ball [Decisioneering Inc.] or @Risk [Palisade] [Haas et al. 1999]. Such programs, however, become difficult to manage as the number of models, and sub-models describing each barrier step increases. This is unfortunate for two reasons. Firstly Excel has the great advantage that most engineers and scientists are sufficiently familiar with its workings to also understand the operation of the probabilistic add-in functions. Secondly because of their transparency, communicating the structure of spreadsheet models is relatively straightforward. The solution found to this was to adapt the concept of the ‘Metamodel’ [e.g. Schimoeller 2004] to an @Risk version 4.5 enhanced workbook program (Section 8.2.7).

The idea of a Metamodel [Harvey, 2005] is that when developing a simulation system, rather than constructing a purpose designed ‘monolithic’ model which runs in isolation, construct first a software framework or domain within which different modules can be inserted or replaced according to needs. The Metamodel based system provided a way of efficiently compiling large numbers of alternate source water concentration, barrier consumption and dose-response sub-models. These were then assembled into the different simulation models for each CTS, pathogen and scenario. The main benefit was that the large number of moderately complex simulation models could be easily managed within an Excel spreadsheet environment. Other benefits included ease of checking for model errors, revision and storage for future use or modification, and recording of reservations relating to data quality for future attention.
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8.2.6 Simulation Model Outputs

Excel add-ins such as @Risk generate a wide range of output statistics with potential to inform a water manager/decision maker. This section describes further those statistics which were found most useful for estimating risk. Most were obtained using standard Excel routines and simple @Risk statistics functions.
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Secondary features of value were @Risk Goal Seek Wizard which was useful for Critical Limit estimation, and the Distribution Fitting wizard which was useful for preliminary estimation of coefficients for PDF functions from sets of pathogen or surrogate concentration data or barrier removal data. This fitting wizard is probably most useful for Tier 1 or perhaps Tier 2 assessments. If possible, and for higher Tiers data should be fitted by the more sophisticated techniques presented in Chapter 7.

The detailed @Risk Output window provided access to the actual output of each model iteration. The @Risk Wizards for Advanced Sensitivity Testing and Stress Analysis were not used for work described here. This is not to suggest that water managers will not find them useful but that they were not essential to the risk assessment tasks here and in Chapter 7.

8.2.6.1 Baseline Risk Estimates

Baseline risks are exposure and risk probability estimates calculated assuming nominal operating conditions i.e. where source waters are not exposed to unusual contamination inputs and treatment processes are operating according to specifications. Simulation risks are expressed in two principle formats:
- Daily probability of infection by pathogen (prob. of infection.person^{-1}.d^{-1}); and
- Annualized infection rates (prob. of infection.person^{-1}.y^{-1}).

As the pathogen risk estimates are by their nature PDFs with variable associated distribution, the following statistics were routinely calculated for each pathogen:
- The arithmetic average of all risk simulation iterations (= Average Risk) which accounts for distribution skew;
- 95th and 99th percentiles which indicated the robustness of the Average Risk estimate; and
- The Median risk that indicated mid-range risk.

8.2.6.2 Factor Sensitivity Values

A full discussion of Factor Sensitivity and its uses is presented in Chapter 7. In this Chapter Sensitivity analyses were undertaken mainly to help indicate:
- Which stages are most critical to maintaining acceptable water quality and hence which should be most closely managed;
- How different stages and barriers compare to one another in importance and variance;
- At which stage(s) might Hazardous Events have a major impact; and
- If it was likely that there may be rare periods of much higher and/or low risk (extremes of PDFs).

Factor Sensitivity is calculated by dividing the daily risk estimate obtained when an input value is set to a credible but extreme value, by the Baseline risk and then log_{10} transforming the ratio to generate ‘Factor Sensitivity’ or FS values [Zwietering and van Gerwen, 2000] i.e. $FS = \log_{10}(\text{average annualized infection risk arising when the baseline model (e.g. PDF for sand filtration) has been substituted with a credible extreme value, divided by the average annualized Baseline infection risk})$.

An indication of Factor Sensitivity can be gleaned by comparing the changes in concentrations of pathogens across different barriers. Further, the Factor Sensitivity calculation standardises the comparison parameter and thereby aids comparison between all barriers.
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8.2.6.3 Additional Risk Arising from a Hazardous Event
Hazard analysis critical control point (HACCP) analysis is being promoted increasingly in the water industry (Chapter 2). Integrating QMRA into this framework is a simple way by which QMRA can be made and accessible to commercial water managers. To this end we have developed an approach for modelling Hazardous Events occurring at Control Points and proposed how Baseline and Hazardous Event modelling can be used to estimate Critical Limits needed at these control points in order not to exceed Tolerable Risk levels.

The daily risk from a Hazardous Event is calculated in the same manner as the Baseline risk estimates. Then because the durations of Hazardous Events vary greatly, a total Baseline+Hazardous Event risk is estimated over an extended period (e.g. 1 year). This is done by simulating in parallel Baseline and Event conditions and then choosing the output of one or other iteration in proportion to the proportion of time spent in each state. The impact of the Hazardous Event is then assessed by comparison of the total risk estimate with the Baseline risk estimate.

8.2.6.4 Critical Limits
Baseline and Baseline+Hazardous Event simulations allow the impact of normal operation and system failures at each Control Point to be quantified and compared to target values. This provides the basis for quantitatively defining and setting Critical Limits or ‘Action Levels’ a central concept in the HACCP process which addresses the need of managers for clear guidance of when a CTS is operating satisfactorily and when it needs attention. Setting of Critical Limits and associated operational (target) limits has various potential uses including:
1. Estimation of tolerable maintenance and failure periods for water treatment barriers;
2. Standard reference points against which safety factors may be develop;
3. Definition of minimum treatment efficiency under Baseline and Hazardous Event conditions which can be used to assess treatment plant function and propose methods to avoid or reduce adverse impacts;
4. Setting of regulatory legislation and guidelines;
5. Measurement of system performance (e.g. in audits); and
6. Simulation of what monitoring parameters will provide information suited to management and whether existing monitoring needs revision.

Two methods for Critical Limit setting were identified, graphing of similar scenarios with variable event duration and the use of @Risk Goal Seek to estimate the performance required of a barrier to achieve a particular target risk value.

8.2.6.5 Monte Carlo Probabilities as Relative and Absolute Estimates of Risk
Risk estimates derived from Monte Carlo style simulation modelling are typically of the form - number of infections.person⁻¹.time period¹. In this form they appear superficially absolute. However, as discussed in Section 8.2.2, they are in fact a best estimate of likely health risks for a population based on a combination of statistical analysis of historical data and intuition rather than a perfect prediction of illness rates in the CTS of interest (Chapter 1). Accordingly the decision maker must recognize that risk estimates can be used either as relative or ‘absolute’ measures and considered this in their use.
Water managers are commonly faced with three basic questions where QMRA risk estimation can be useful:
- Where action has been determined necessary, what is the preferred option out of a number of choices?
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- Where monitoring (new research or ongoing audit) data has been gathered, do the results indicate a need for action based on an explicit existing triggers or general principles?
- Where there are social concerns and calls to initiate water management, what advice should be given to senior management and communications departments as to whether action is warranted?

In the first instance QMRA is well suited to providing the relative assessments required as it implicitly weights the benefits and limitations of different technical options. For example it allows the effectiveness of two treatment processes to be compared or two sources of risk. It also allows the severity of different Events to be compared to one another and to the general Baseline Risk, and hence whether a given risk is likely to be of concern.

In the second and third instances, prediction of ‘absolute’ risks is not possible for reasons described by Dowie [2005]. What can be provided is still arguably the best estimate possible of the absolute risk probability estimate based on scientific data.

8.2.7 Model Coding

QMRA models for simulating pathogen reduction, consumption and infection were constructed using MS Excel program v. 8 [2002] enhanced with @Risk v. 4.5 [Palisade, Ithaca, NY]. As discussed earlier the program was designed using the Metamodel concept whose relevance for environmental and risk management has been discussed by Harvey [2005] in respect to hydrological modelling.

The procedure for constructing a Baseline risk simulation model was as follows: Excel was enhanced with the @Risk 4.5 Professional Add-in;
A quantitative probabilistic model describing each simulation stage/barrier was developed and entered as a single Excel table record (i.e. one line in a worksheet table);
Specific QMRA stage/barrier models were then assembled in a ‘Scenario’ worksheet. This was achieved using Excel “Lookup and Reference” functions such as Indirect() and Offset() to extract each stage/barrier model in a sequence reflecting CTS structure;
The final model was run using the @Risk Start Simulation tool; and
Infection rate, Factor Sensitivity, and Critical Limit output data were generated using the RiskOutput() and @Risk statistics functions.

Typically each barrier/stage model comprised a) descriptive information such as algorithm source and pathogen and b) algorithms comprised of @Risk Distribution functions and lookup tables which together generated a probability density function which defined stage/barrier process. Different primary tables were constructed to store source water concentration, barrier performance, consumption and dose-response models. Using this system it was possible to rapidly assemble QMRA models and explore model variations e.g. by constructing and selecting alternate barrier functions, dose-response curves etc.

Calculation of the impact of Hazardous Events required an additional ‘Event Scenario’ module. This module was run in parallel with the Baseline Scenario module. The outputs of the two modules were then sampled in proportion to the fraction of time the CTS was in its Baseline or Hazardous Event state. Risks were then combined using the procedure summarised in Figure Error! No text of specified style in document.-3. The effect was to
simulate infection risk PDF function distribution similar to the Baseline but with a few high risk outlier values with potentially large influence over the aggregate average infection rates.

This sub-model library and selective extraction design features had a range of benefits compared to a series of specific task models. Reuse of a common framework allowed extensive familiarisation, design refinement and checking for errors. It was possible to rapidly recreate older models for review and updating as well as to rapidly build new barrier models by copying an existing structure and altering the model descriptors and function coefficients. When modifications were introduced, older modules could be maintained as a contingency. As a result only one moderate sized workbook was required to accommodate the full range of MicroRisk models. Also, recording of risk scenario settings for documentation and further use was straightforward.

8.3 CTS 8: AN ILLUSTRATIVE EXAMPLE

This section presents the inputs and outputs for CTS 8 to illustrate the modelling process and outcomes associated with Baseline risk estimation. It identifies and discusses key features of each barrier and shows how the data can be interpreted.

8.3.1 System Conceptualisation

Initial steps in developing a general modelling scheme for CTS 8 are covered in detail in Chapter 7. Using the information collected the critical stages and barriers in the water supply system were defined (Table Error! No text of specified style in document.-1, Figure Error!)
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No text of specified style in document.-1). In developing the Baseline models the following principles were employed:

2. Use the best available local data when defining each barrier/stage;
3. Where there are a choice of stage/barrier PDFs more conservative ones based on local data should be preferred;
4. Remove Hazardous Events data from Baseline datasets except where the data is insufficient and/or Events data too ill-defined to include in Baseline scenario;
5. Assume the CTS operates in a linear fashion, with each barrier functioning independently to treat the product of the previous barrier; and
6. Where ‘Absolute’ Risks are to be estimated, threshold targets values should be identified first to minimise interpretation biases.

The first practical step was to fix the starting point of the simulations, i.e. the Source Water location and its attributes. Two options were considered. Pathogen and indicator data were available for the CTS 8 reservoir (see Chapter 3) and the CTS 8 river immediately upstream of the reservoir. The river water dataset was chosen because it provided a very well defined starting point, downstream of the most impacted land, *Campylobacter* were present in significant concentrations allowing estimation of PDF coefficients under dry and wet conditions, and 10 minute hydrologic data was available allowing differentiation of high run-off event periods.

The next step was to define each barrier conceptually and quantitatively. For each barrier a probability density function (PDF) was constructed, which generated a spread of log_{10} decimal elimination capacity (DEC) factors [Hijnen et al. 2005] when sampled in a Monte Carlo fashion. All four barriers (the CTS 8 reservoir, the system flocculation-coagulation-dissolved air flotation (F/C/DAF) unit, the rapid sand filter (RSF) and the chlorination) were similarly definable. There was no large contact chlorination tank, however, water was stored on site for several hours providing an opportunity for chlorine mediated inactivation to take place. Nonetheless, data on storage tank operating temperature, flow and filling cycles was available.

Consideration of the source water and barrier data showed that in general a Tier 3 level risk assessment was possible. As this would not always be the case we also undertook Tier 1 and Tier 2 simulations and these are presented for illustrative & comparison purposes. The considerations, analysis principles, programming and data management methods applied equally to Tiers 1, 2 and 3 style simulations. The main difference in the simulations was the origin and form of the input data.

Once assembled the Tier 1, 2 and 3 data were entered into the Excel sub-model library tables. Simulations were undertaken using the default @Risk settings (Latin hypercube sampling, randomly generated seed) to generate final infection risk rates. Run times ranged from ca 30 seconds for 1000 simulation iterations to 2 hours for 100 000 on a later model PC (1024 Gigabytes RAM, 1400 gigahertz Centrino Processor, Windows XP). Repeated simulations showed that there was little difference in the Baseline risk estimates generated by 1000 and 10 000 iterations.

8.3.1.1 Tier 1 and Tier 2 Input Data

Tier 1 and Tier 2 data were obtained from the same sources but were used in slightly different ways to compare and contrast the outputs. With the exception of the source water
concentration data all were generic and readily available. Source water quality data was taken as the *Campylobacter* concentration data collected during dry weather conditions. From this dataset the 5th percentile, mode and 95th percentile were estimated. Barrier removal for bacteria were obtained from three literature sources [LeChevallier and Au, 2004; Hijnen et al., 2005; Westrell et al., 2003]. Again the 5th percentiles, modes and 95th percentiles were estimated. Consumption used the default Melbourne Australia PDF recommended by Mons et al. [2005]. The dose-response relationship used the *Campylobacter* beta Poisson curve in Haas and Eisenberg’s [2001] summary table.

8.3.1.2 Tier 3 Input Data

No measurements were made of *Campylobacter* in the reservoir because it was judged from protozoa inactivation rates that their concentration would be too low to usefully estimate with the available assay technology (sensitivity ca 1 bacteria L⁻¹). Instead the long timeseries data set of *E. coli* concentrations at the water treatment plant off-take was combined with *E. coli* data for the river to estimate a reduction factor distribution function for vegetative coliform-like bacterial cells. F/C/DAF and RSF removal were estimated by measuring Total Coliforms concentrations before and after each of these processes.

Independent analytical support for the DEC probability density function soundness was obtained in the case of the reservoir, F/C/DAF and RSF barriers. In the reservoir, reduction in the much more durable *Cryptosporidium* was observed to be ca 1.4 orders of magnitude. The removal estimates for bacteria by the physical water treatment plant processes were consistent with the experimentally observed removal of inoculated *Saccharomyces cerevisiae* and particles in size band ranges between 1 and 20 µm. It was not possible to confirm disinfection inactivation rates, but sufficient information on flow, water temperature, chlorine concentration and storage tank operation were available to use the conservative Complete Stirred Tank Reactor (CSTR) equation proposed in Chapter 4 from estimating chemical disinfection barrier effectiveness.

Reduction in concentration within the distribution system was included in the Baseline simulations as conceptually water should have been fit to drink at the exit from the treatment plant and no further disinfection should ideally have been required. Distribution ingress was seen as better modelled as a class of Hazardous Event. Other reasons were that distribution system was not conceptually an inactivation barrier, no inactivation model was available and data on pathogen presence was very limited (see Chapter 5).

Good estimates of local consumption rates were available from Mons et al. [2005] who included, among their reported PDFs, functions for South Australia where CTS 8 was located. Several dose-response relationships were reviewed. That selected [Van den Brandhof et al. 2003] was conservative (i.e. *Campylobacter* assumed to be highly infectious) and most recent in derivation.
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Table Error! No text of specified style in document. 1. CTS 8 Stages and Barriers Described Quantitatively

<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Stage/Barrier Description</th>
<th>Input Data Origin (Tier 3)</th>
<th>How Stage Modeled in Maximum Detail (Tier 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Source Water</td>
<td>River water running off an intensively developed agricultural catchment. Catchment water quality and quantity modelled based on microbial quality and flow measurements taken over a total period of ca 3 years from the key stream monitoring station located immediately above its entry point to the CTS 8 reservoir.</td>
<td>Primary input information was concentrations of <em>Campylobacter</em> spp. measured during dry and wet weather during different seasons and years. <em>Campylobacter</em> probability density functions were estimated for dry and wet weather. The proportion of time that the river was under dry or wet weather flow was calculated as a proportion of each season. The source PDF inputted into the model was designed to select values from one to the eight possible states (4 seasons X dry and wet weather flow conditions).</td>
<td>The PDFs for of <em>E. coli</em> concentrations in the river under dry and wet weather conditions are combined with flow data to estimate the total loads entering the reservoir during each season and average initial concentration in the reservoir headwaters. This is then compared with the seasonal <em>E. coli</em> concentrations at the extraction point to estimate a seasonal reduction (DEC) factor. Three treatment modules were monitored over the course of a full water production cycle (production is effective in batches due to Rapid Sand Filtration cycles). Reductions in total coliform concentrations were measured used to estimate the DEC function. Three treatment modules were monitored over the course of a full batch treatment run. Reductions in total coliform concentrations were measured used to estimate the DEC.</td>
</tr>
<tr>
<td>Barrier A</td>
<td>Large reservoir designed primarily to store winter rains and minimize the impact of drought.</td>
<td>Reduction in <em>Campylobacter</em> spp. concentration by natural processes (e.g. predation, thermal inactivation) based on the observed reduction in <em>E. coli</em> concentration between source water station located at the head of the Reservoir and the Water Treatment Plant intake.</td>
<td></td>
</tr>
<tr>
<td>Barrier B</td>
<td>Dissolved Air Flotation treatment stage designed to remove the majority of flocculated and coagulated particles (Alum, polymer coagulant)</td>
<td>Reduction in <em>Campylobacter</em> based on reductions in total coliform concentrations measured between the beginning of the F/C/DAF process mixing zone and underside of the DAF sludge layer.</td>
<td>Three treatment modules were monitored over the course of a full water production cycle (production is effective in batches due to Rapid Sand Filtration cycles). Reductions in total coliform concentrations were measured used to estimate the DEC function.</td>
</tr>
<tr>
<td>Barrier C</td>
<td>Rapid Sand Filter designed to remove particles remaining after the DAF process on a batch cycle of 10-20 hours.</td>
<td>Reduction in <em>Campylobacter</em> based on reductions measured in total coliform concentration above and below the sand filter</td>
<td>Three treatment modules were monitored over the course of a full batch treatment run. Reductions in total coliform concentrations were measured used to estimate the DEC.</td>
</tr>
<tr>
<td>Barrier D</td>
<td>Chlorination + on plant storage</td>
<td>Reduction in bacterial concentration is estimated using a combination of local and literature data and other information. Chlorine inactivation kinetics use published inactivation coefficients. Local measurements of water temperature, total production flow rate, tank volume and filling/emptying statistics. Disinfection was modelled assuming continuously stirred tank reactor conditions apply.</td>
<td>Key equations were: Decimal (log10) elimination capacity = log10 (1/(1+(Concentration Cl2 * Contact time)<em>(1st order reaction constant k'))) (Cl2 concentration * Contact time) = [Cl2]</em>[Storage Volume]<em>[Fraction of storage tank full]/[Flow rate] k = A</em>e^(-E/(R.T))</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Stage/Barrier Description</th>
<th>Input Data Origin (Tier 3)</th>
<th>How Stage Modeled in Maximum Detail (Tier 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption</td>
<td>Daily consumption of cold tap water person</td>
<td>Australian state specific drinking water consumption pattern.</td>
<td>Consumption rate modeled as a Poisson distribution</td>
</tr>
<tr>
<td>Dose Response</td>
<td>Dose-response curve for <em>Campylobacter</em> infection rate.</td>
<td>Dose-response curve calculated from multiple sources including outbreak data.</td>
<td>Beta Poisson dose-response curve + Maximum risk curve (where the infection probability calculated from beta Poisson is greater than that for the Maximum Risk Curve, see Chapter 7)</td>
</tr>
</tbody>
</table>
8.3.2 CTS 8 Baseline Risk Estimation Based on Stage / Barrier Simulations

8.3.2.1 Tier 1

The Tier 1 simulation first used mid-range point values (Table Error! No text of specified style in document.-2) to estimate the risks of infection arising from consumption of drinking water. The Average Risk probability estimates were $1.0 \times 10^{-8}$, person$^{-1}$,d$^{-1}$ and $3.7 \times 10^{-6}$, person$^{-1}$,y$^{-1}$ corresponding to an overall reduction in *Campylobacter* concentration by a factor of $6 \times 10^{7}$. This high level of removal and the fact that the annualised risk of infection was much less than the mooted Benchmark probability of $1.0 \times 10^{-4}$, person$^{-1}$,y$^{-1}$ [Hunter and Fewtrell 2001; Chapter 2] suggested that the water quality achieved was satisfactory.

However when more conservative ‘worst case’ inputs were used as is done in the case of chemical exposures (e.g. CMPHU 2005) the equivalent risk probability estimates were $6 \times 10^{-2}$, person$^{-1}$,d$^{-1}$ and 1.0, person$^{-1}$,y$^{-1}$. This was despite the fact that worst case values were not used for dose-response and water consumption. The difference between the mid-range and worst case scenarios highlights the uncertainty associated with point value simulations and their sensitivity to input values chosen.

Nonetheless, Tier 1 style screening still had value. If the mid-range risk estimates had been judged to be high then more detailed conservative simulations would most likely have yielded the same result and need for some action would require little further confirmation. Similarly if the worst case simulation showed risk to be low then the real risk would be likely to be very low and remedial action would not be required and further simulations would be unnecessary.

In the present instance though the risk estimates provided very different conclusions regarding risk. In this case the appropriate response to enhance the quality of the statistical assessment was to move to a Tier 2 assessment.

The annualised Average Risk values equate approximately to the commonly seen “n$$_{1}$ infections per n$$_{2}$ population per year”. In the current instance (Average Risk probability $3.7 \times 10^{-6}$, person$^{-1}$,y$^{-1}$) the equivalent mid-range value would be “0.037 infections per 10 000 persons per year”. The individual infection risk probability measures ($10^{\text{power}}$) were used as the primary simulation output format because the meaning of the “infections per 10 000” style formats are ambiguous where the probability of multiple infections per year is significant.

<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Simple and/or Literature Functions Describing Stage/Barrier</th>
<th>Mid Range Input Values</th>
<th>Worst Case Input Values</th>
<th>Rationale for Choices</th>
<th>Information Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Source Water</td>
<td>Dry weather probability density function for <em>Campylobacter</em> L$^{-1}$ is described by the following statistics: Median = 43, 95$^{th}$ percentile = 903</td>
<td>Measurements of pathogen concentration will tend to be undertaken under dry weather conditions. Ten to 20 measurements would</td>
<td>Dry weather data from CTS 8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### How to implement QMRA

<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Simple Literature Functions Describing Stage/Barrier</th>
<th>Mid Range Input Values</th>
<th>Worst Case Input Values</th>
<th>Rationale for Choices</th>
<th>Information Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Barrier A</strong> (Reservoir)</td>
<td>Decimal elimination capacity (DEC) with the following coefficients:</td>
<td>Mode = 1.45</td>
<td>Minimum = 0.70</td>
<td>be considered a good sized small sample set.</td>
<td>LeChevallier and Au [2004] Bacterial reduction in reservoirs (Chapter 3)</td>
</tr>
<tr>
<td><strong>Barrier B</strong> (Coagulation + Flocculation + DAF)</td>
<td>Triangular DEC with the following coefficients:</td>
<td>Mode = 1.55</td>
<td>Minimum = 0.55</td>
<td>Conservative removal based on literature data on flocculation removal of bacteria.</td>
<td>Hijnen et al. [2005] collation</td>
</tr>
<tr>
<td><strong>Barrier C</strong> (Rapid Sand Filter)</td>
<td>DEC with the following coefficients:</td>
<td>Mode = 1.29</td>
<td>Minimum = 0.1</td>
<td>Conservative removal based on literature data on rapid sand filtration removal of bacteria.</td>
<td>Hijnen et al. [2005] collation</td>
</tr>
<tr>
<td><strong>Barrier D</strong> (Chlorination + Short term storage)</td>
<td>DEC with the following coefficients:</td>
<td>Mode = 3.5</td>
<td>Minimum = 2.5</td>
<td>Removal based on literature data on chlorination reduction of bacteria</td>
<td>Westrell et al. [2003]</td>
</tr>
<tr>
<td><strong>Consumption</strong></td>
<td>PDF of litres consumed per day per person (Consumption PDF) with the following statistics: 5&lt;sup&gt;th&lt;/sup&gt; percentile = 0 L; Mode = 0.75 L; 95&lt;sup&gt;th&lt;/sup&gt; percentile = 1.5 L</td>
<td></td>
<td></td>
<td>Recommended as a default value in the absence of local consumption data</td>
<td>Mons et al. [2005] Poisson based on conservative data for Melbourne Australia</td>
</tr>
<tr>
<td><strong>Dose-response</strong></td>
<td>[ P = 1 - (1 + (dose/896)^{(2^{(\theta_{10.145-1})})})^{-0.145} ]</td>
<td></td>
<td></td>
<td>Widely available reference making de facto choice</td>
<td>Haas and Eisenberg [2001] Table 8.1</td>
</tr>
</tbody>
</table>

Note:
No special point estimates were used for consumption and dose-response as this would be unnecessary in practice because of the extent of data now available (Chapter 7).

8.3.2.2 **Tier 2**
Tier 2 employed simple PDFs (Table Error! No text of specified style in document.-3) to estimate the order of magnitude of risk. The Average Risk probability estimates 2.0x10<sup>-7</sup>.person<sup>-1</sup>.d<sup>-1</sup> and 7.4x10<sup>-5</sup>.person<sup>-1</sup>.y<sup>-1</sup>. The annualized risk of infection was considerably higher than the point value supporting the (simulated) decision to undertake a higher Tier assessment.

The Average annualised risk probability also approached the mooted Benchmark of 1.0x10<sup>-4</sup>.person<sup>-1</sup>.y<sup>-1</sup> (Chapter 2) suggesting that the water quality achieved was satisfactory. Yet bearing in mind that the Tier 2 estimate is still not an optimal simulation, a conservative decision maker using the 1.0x10<sup>-4</sup> value as a Benchmark might desire further evidence before finalising a decision on whether further management was needed. One possible response in this case would be to undertake a Tier 3 assessment based on more appropriate inputs to determine whether a similar conclusion on risk would be reached.
### 8.3.2.3 Tier 3

Using the complete set of available data a range of functions and coefficient values were developed to quantify the effectiveness of each barrier (Table Error! No text of specified style in document.-4) and produce Tier 3 risk estimate statistics (Table Error! No text of specified style in document.-5). Though the analysis was superficially similar to that undertaken for Tier 2, the data inputs and barrier models can be seen from Table Error! No text of specified style in document.-4 to be much more complex reflecting the local origin of the data and mechanistic barrier behaviour functions. The final calculation products were the daily and annualised Average Risk estimates (risk probability $\text{Campylobacter infection } 4.8\times10^8 \text{.person}^{-1}\text{.d}^{-1}/1.7\times10^5 \text{.person}^{-1}\text{.y}^{-1}$).

<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Simple and/or Literature Functions Describing Stage/Barrier</th>
<th>Rationale for Choice</th>
<th>Information Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input Source</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>Dry weather probability density function for $\text{Campylobacter.L}^{-1}$ is described by the following statistics: 5th percentile = 2; Median = 43; 95th percentile = 903</td>
<td>Measurements of pathogen concentration will tend to be undertaken under dry weather conditions. Ten to 20 measurements would be considered a good sized small sample set.</td>
<td>Dry weather data from CTS 8</td>
</tr>
<tr>
<td><strong>Barrier (Reservoir) A</strong></td>
<td>Uniform decimal elimination capacity (DEC) with the following coefficients: Minimum = 0.70; Maximum = 2.2; (Mode) = 1.45</td>
<td>The minimum and maximum are reductions in bacteria reported to occur in reservoirs</td>
<td>LeChevallier and Au [2004] Bacterial reduction in reservoirs (Chapter 3)</td>
</tr>
<tr>
<td><strong>Barrier (Coagulation + Flocculation + DAF) B</strong></td>
<td>Triangular DEC with the following coefficients: Minimum = 0.55; Maximum = 3.7; Mode = 1.55</td>
<td>Conservative removal based on literature data on flocculation removal of bacteria.</td>
<td>Hijnen et al. [2005] collation</td>
</tr>
<tr>
<td><strong>Barrier (Rapid Filter) C</strong></td>
<td>Triangular DEC with the following coefficients: Minimum = 0.1; Maximum = 3.4; Mode = 1.29</td>
<td>Conservative removal based on literature data on rapid sand filtration removal of bacteria.</td>
<td>Hijnen et al. [2005] collation</td>
</tr>
<tr>
<td><strong>Barrier (Chlorination + Short term storage) D</strong></td>
<td>Triangular DEC with the following coefficients: Minimum = 2.5; Maximum = 5.0; Mode = 3.5</td>
<td>Removal based on literature data on chlorination reduction of bacteria.</td>
<td>Westrell et al. [2003]</td>
</tr>
<tr>
<td>Consumption</td>
<td>PDF of litres consumed per day per person described by Poisson distribution with the following coefficient: Gamma = 3.37</td>
<td>Recommended as a default value in the absence of local consumption data</td>
<td>Mons et al. [2005] Poisson based on conservative data for Melbourne Australia</td>
</tr>
<tr>
<td><strong>Dose-response</strong></td>
<td>$P=1-(1+(dose/896)^{(2^{(1/0.145-1)})})^{0.145}$</td>
<td>Widely available reference making de facto choice</td>
<td>Haas and Eisenberg [2001] Table 8.1</td>
</tr>
</tbody>
</table>
A range of features can be seen in the Tier 1, 2, and 3 input and output data (Tables 8-2 to 8-4) which will be commonly encountered:

- Source water pathogen concentrations are highly variable;
- Pathogen measurement is most useful for characterising source water concentrations;
- Useful barriers need to reduce microbial concentrations by at least one or two factors of 10;
- The output data from each barrier simulation is itself a probability density function whose statistics can be extracted to provide insight into relative barrier effectiveness;
- Describing the behaviour of a barrier may require a complex algorithm or model as in the case of disinfection. The complexity required for the illustrated level of QMRA simulation is within the capacity of water managers moderately skilled in Excel;
- Dose-response curves currently available still have limitations (Chapter 7); and
- Simulations require collection and interpretation of substantial quantities of information. Accordingly good data management and documentation are essential.

### 8.3.3 Comparison of Simulation Tier Outputs

Side by side comparison of the outputs of the three simulation Tiers is shown in Table Error! No text of specified style in document.-6 and Table Error! No text of specified style in document.-7. Overall the lower Tier 1 (mid-range) and two subsequent simulations yielded similar risk estimates the other Tiers, though the estimated influence of the same barrier or stage varied considerably between each simulation (compare concentrations inputted into Dose-response stage). The fact that Tier 2 and Tier 3 yielded similar risk estimate values suggests intuitively that the estimations are robust and could be used as reference points for assessing the impact of Hazardous Events or for comparison with other treatment systems assessed in a similar manner.

The issue of whether risk was very much less or greater than the Average Annualised $10^{-4}$ value was largely resolved. As far as it was possible to determine the average annualised risk was below this mooted Benchmark value though only by an order of magnitude. As to whether it necessitated management intervention would depend on how risk averse the exposed community and supply manager were and how much of a safety margin they desired. The latter might be based on the 95th percentile.

The sequential application of Tier 1, 2 and 3 appeared to work well. The iterative decision sequence simulated (summarised in Chapter 7) addresses in principle a key question for water managers intending to do risk assessment – “How far should QMRA be undertaken on any given CTS?”. The generic answer is, as far as is necessary to provide the manager with sufficient information to make an informed recommendation or decision on the need for water management consistent with their policy on what levels of risk are tolerable, the remediation options available and other decision affecting factors such as resources.

One minor difficulty encountered with the Tier classification scheme was that the best data available for any given CTS could fit into more than one Tier. In the illustrative CTS 8 Baseline simulation the river water concentration inputs were of Tier 3 quality, whereas the dose-response curve reduced to a single threshold infection fraction and was at best Tier 2. As a result the case for assigning the equivalent of Tiers on a barrier by barrier basis was investigated using the CTS 8 simulations. A composite ‘Data Audit’ [Hunter and Fewtrell, 2001] score was assessed for each barrier using criteria shown Appendix 1. The latter were
developed with each ideal Tier assessment in mind. The resulting Data Audit scores are shown in Table Error! No text of specified style in document.-7. The scores were as expected marginally lower than the nominal Tier in the case of the Tier 2 and Tier 3 assessments.
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### Table: Stage and Barrier Input and Output Values for a Tier 3

<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Functions and Coefficients Describing Stages and Barriers</th>
<th>Calculated Pathogen Quantity at Stage Endpoint</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Source Water</td>
<td>Dry weather concentration <em>Campylobacter</em>.L⁻¹ described by a lognormal PDF with coefficients: ( \mu (\log_{10}) = 1.46; \sigma (\log_{10}) = 1.85 )</td>
<td><em>Campylobacter</em>.L⁻¹ intermediate output PDF statistics describing river water were: 5th percentile = 30; Average = 270; 95th percentile = 855 (note these represent a combination of the 4 seasons and the dry and wet data)</td>
<td>Signor <em>et al.</em> [2005]</td>
</tr>
<tr>
<td></td>
<td>Wet weather <em>Campylobacter</em>.L⁻¹ concentration described by a Gamma PDF distribution with coefficients: ( \alpha = 1.98; \beta = 24.7 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Proportion of time in dry weather based on flow analysis: Spring = 0.16; Summer = 0.017; Autumn = 0.065; Winter = 0.329</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barrier A (Reservoir)</td>
<td>Point estimates for seasonal decimal (log₁₀) elimination capacity (DEC’s) were: Spring = 2.69; Summer = 2.46; Autumn = 2.16; Winter = 2.37 These reductions were averaged to generate the reduction figure used.</td>
<td><em>Campylobacter</em>.L⁻¹ intermediate output PDF statistics describing water harvested at the treatment plant inlet were: Median = 0.44; Average = 1.03; 95th percentile = 3.2</td>
<td>(South Australia Water + Signor Ph.D. data)</td>
</tr>
<tr>
<td>Barrier B (Coagulation + Flocculation + DAF)</td>
<td>DEC described by a normal PDF: ( \mu = 2.38; \sigma = 0.38 )</td>
<td><em>Campylobacter</em>.L⁻¹ intermediate output PDF statistics describing water after DAF treatment were: Median = 0.0019; Average = 0.0061; 95th percentile = 0.021</td>
<td>(United Water + Signor Ph.D. data)</td>
</tr>
<tr>
<td></td>
<td>Decimal (i.e. log₁₀) reduction statistics are: 5th percentile = 1.75; Mode = 2.38; 95th percentile = 3.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barrier C (Rapid Sand Filter)</td>
<td>DEC described by a normal PDF: ( \mu = 1.12; \sigma = 0.40 )</td>
<td><em>Campylobacter</em>.L⁻¹ intermediate output PDF statistics describing water after Rapid Sand Filtration were: Median = 7.0x10⁻⁴; Average = 1.4x10⁻⁴; 95th percentile = 2.5x10⁻³</td>
<td>(United Water + Signor Ph.D. data)</td>
</tr>
<tr>
<td></td>
<td>Decimal (i.e. log₁₀) reduction statistics are: 5th percentile = 0.46; Mode = 1.12; 95th percentile = 1.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barrier D (Chlorination + Short term storage)</td>
<td>Complex DEC with the following statistics: A = 6.31E9; E = 48699; R = 8.314; T = 273 + Temperature in °C where °C was obtained by re-sampling of a table of percentiles of water temperature entering the water treatment plant; ([Cl_2]) mg.L⁻¹ = lognormal PDF with ( \mu = 3.86; \sigma = 0.44; ) correction factor = -2.13; Fraction of storage volume = 0.1*beta function; Flow (ML.d⁻¹) = resample of percentile lookup table of flows into the plant.</td>
<td><em>Campylobacter</em>.L⁻¹ intermediate output PDF statistics describing water after chlorination were: Median = 1.3x10⁻⁵; Average = 9.9x10⁻⁵; 95th percentile = 3.7x10⁻⁷</td>
<td>(Kiwa CSTR disinfection model, and local flow, temperature chlorine and reservoir %full data)</td>
</tr>
<tr>
<td></td>
<td>Coefficients and inputs used in reduction calculation were:</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Consumption PDF of litres consumed per day per person described by Poisson distribution with the following coefficient: Gamma = 2.86</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Functions and Coefficients Describing Stages and Barriers</th>
<th>Calculated Pathogen Quantity at Stage Endpoint</th>
<th>Data Source</th>
</tr>
</thead>
</table>
| Dose-response   | 5<sup>th</sup> percentile = 0 L; Mode = 0.75 L; 95<sup>th</sup> percentile = 1.5 L  
Variation on beta Poisson where dose is always 0 or 1:  
Prob. of infection (P) = $e^{-(\alpha/\alpha + \beta) \times \text{Dose}}$  
Where beta = 0.011 and alpha = 0.024  
The Maximum likelihood curve is: $P = 1 - e^{-(\text{Dose})}$ | PDF statistics describing probability of *Campylobacter* infection, person<sup>-1</sup>, day<sup>-1</sup> after full treatment are:  
Median = 5.410<sup>-9</sup>; Average = 4.1x10<sup>-8</sup>; 95<sup>th</sup> percentile = 1.8x10<sup>-7</sup> | [Van den Brandhof et al., 2003; Evans et al. 1996; Teunis pers. Com] |
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Table Error! No text of specified style in document.-5. Final Tier 3 CTS 8 Baseline Risk Estimate Statistics for Campylobacter

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Average</th>
<th>Median</th>
<th>95th percentile</th>
<th>99th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of infection (person.d⁻¹)</td>
<td>4.8x10⁻⁸</td>
<td>4.9x10⁻⁹</td>
<td>2.6x10⁻⁷</td>
<td>1.1x10⁻⁶</td>
</tr>
<tr>
<td>Annualised probability of infection (person⁻¹.y⁻¹)</td>
<td>1.7x10⁻⁵</td>
<td>1.8x10⁻⁶</td>
<td>6.5x10⁻⁵</td>
<td>4.0x10⁻⁴</td>
</tr>
</tbody>
</table>

Notes:
Statistics calculated from Monte Carlo simulation outputs.
Annual estimates calculated using equivalent daily estimate for that statistic using the equation $P_{ann} = 1-(1-P_{daily})^{365}$.

Table Error! No text of specified style in document.-6. Average Output of Each CTS 8 Stage/Barrier Simulated with Different Tier Data

<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Units</th>
<th>Average Output of Each Barrier Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Tier 1 Mid range Case</td>
</tr>
<tr>
<td>Input Source Water</td>
<td>Campylobacter.L⁻¹</td>
<td>43</td>
</tr>
<tr>
<td>Barrier A (Reservoir)</td>
<td>Campylobacter.L⁻¹</td>
<td>1.5</td>
</tr>
<tr>
<td>Barrier B (Coagulation + Flocculation + DAF)</td>
<td>Campylobacter.L⁻¹</td>
<td>4.3x10²</td>
</tr>
<tr>
<td>Barrier C (Rapid Sand Filter)</td>
<td>Campylobacter.L⁻¹</td>
<td>2.2x10⁻³</td>
</tr>
<tr>
<td>Barrier D (Chlorination + Short term storage)</td>
<td>Campylobacter.L⁻¹</td>
<td>7.0x10⁻⁷</td>
</tr>
<tr>
<td>Consumption</td>
<td>Campylobacter.d⁻¹</td>
<td>5.9x10⁻⁷</td>
</tr>
<tr>
<td>Dose-response</td>
<td>Campylobacter.infection. person⁻¹.d⁻¹</td>
<td>1.0x10⁻⁸</td>
</tr>
<tr>
<td>Annualized Risk</td>
<td>Campylobacter.infection. person⁻¹.y⁻¹</td>
<td>3.7x10⁻⁶</td>
</tr>
</tbody>
</table>

Table Error! No text of specified style in document.-7. Comparison of final Risk Statistics Estimated for CTS_8 Using the Four Alternative Tier Value Input Date Sets

<table>
<thead>
<tr>
<th>General Level</th>
<th>Tier Assessment</th>
<th>Probability of infection.person⁻¹.d⁻¹</th>
<th>Data Audit Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Median</td>
<td>95th percentile</td>
<td></td>
</tr>
<tr>
<td>Tier 1 – Point Values (mid range)</td>
<td>1.0x10⁻⁸</td>
<td>9.3x10⁻⁹</td>
<td>2.2x10⁻⁸</td>
</tr>
<tr>
<td>Tier 1 – Point Values (worst case)</td>
<td>6.0x10⁻²</td>
<td>6.4x10⁻²</td>
<td>1.2x10⁻¹</td>
</tr>
<tr>
<td>Tier 2 – Uniform or Triangular Distributions</td>
<td>2.0x10⁻⁷</td>
<td>6.5x10⁻⁹</td>
<td>7.7x10⁻⁷</td>
</tr>
<tr>
<td>Tier 3 – Best available location specific modelling Inputs</td>
<td>4.1x10⁻⁸</td>
<td>4.9x10⁻⁹</td>
<td>2.6x10⁻¹</td>
</tr>
</tbody>
</table>

Note.
1. The slight variability in the ‘point estimate’ risks arises from the use of the default consumption distribution function.

8.4 EXTENSION OF THE RISK ESTIMATION PROCESS

Once a Baseline CTS model and Scenario have been developed it could be systematically expanded and altered to explore the sources and importance of the different factors.
contributing to pathogen risks. Three stages in this process are considered in this section using CTS 8 again as the principle example:

- Factor Sensitivity Analysis;
- Simulation of Hazardous Events; and
- Estimation of Critical Limits.

### 8.4.1 Sensitivity Analysis

Sensitivity Analysis was undertaken by replacing the Tier 3 PDFs with point values based on our knowledge of CTS 8. Bearing in mind the need to move away from intuited probabilities, selection or ‘extreme values’ posed a challenge. In the end the criteria adopted were:

- 95th or 99th percentiles of PDFs or equivalent.
- Extreme values observed in the literature for similar CTS barriers or stages.
- Worst long term barrier failure based on the team’s expert opinion.
- Default maximum values (= total barrier failure, maximum conceivable water consumption (taken as 6 Litres per day), maximum infectivity).

Comparison of the FS values (Table Error! No text of specified style in document.) indicated that for *Campylobacter* the most critical were the disinfection barrier followed by the reservoir. Four stages showed FS values > 1 log_{10} units and hence the potential for markedly increasing long term risk if they were not functioning nominally. This analysis also indicates that management of all stages upstream of consumption was important in protecting consumers, as under poor conditions all could lead to degradation of treatment by an order of magnitude or more.

These FS scores provided a rational order for prioritising investigations and water treatment plant upgrades. In the case of CTS 8 understanding and improving chlorination appears to be the best way to improve protection against *Campylobacter* infection in the consumer population, followed by reservoir management.

A related use of this priority list is to identify where Hazardous Events might have the most severe effects and where impact modelling and Critical Limit development would be most useful.

<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Sensitivity Value Tested</th>
<th>Average Tier 3 Baseline</th>
<th>Sensitivity Value Inputted</th>
<th>Average FS Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Source Water</td>
<td>95th percentile Tier 3 Baseline <em>Campylobacter</em>L^{-1}</td>
<td>270</td>
<td>2500</td>
<td>1.01</td>
</tr>
<tr>
<td>Barrier A (Reservoir)</td>
<td>Decimal Reduction due only to dilution arising when input flows short circuit [Hipsey et al. 2005]</td>
<td>2.42</td>
<td>1.0</td>
<td>1.48</td>
</tr>
<tr>
<td>Barrier B (Coagulation + Flocculation + DAF)</td>
<td>Worst Case Decimal Reduction “expert opinion”</td>
<td>2.38</td>
<td>1.0</td>
<td>1.32</td>
</tr>
<tr>
<td>Barrier C (Rapid Sand Filter)</td>
<td>Worst Case Decimal Reduction “expert opinion”</td>
<td>1.12</td>
<td>0.2</td>
<td>0.82</td>
</tr>
<tr>
<td>Barrier D (Chlorination + Short term storage)</td>
<td>Worst Case Decimal Reduction “expert opinion”</td>
<td>3.88</td>
<td>1.0</td>
<td>2.92</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Stage/Barrier</th>
<th>Sensitivity Value Tested</th>
<th>Average Tier 3 Baseline</th>
<th>Sensitivity Value Inputted</th>
<th>Average FS Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption</td>
<td>Extreme High Consumption Netherlands (litres)</td>
<td>0.75</td>
<td>6</td>
<td>0.90</td>
</tr>
<tr>
<td>Dose-Response</td>
<td>Maximum infectivity</td>
<td>0.6 infections per organism</td>
<td>( P=1-e^{-\text{dose}} )</td>
<td>0.44</td>
</tr>
</tbody>
</table>

### 8.4.2 Hazardous Event Characterization

Simulation of a Hazardous Event involved the following steps:

- Quantitative definition of event characteristics;
- Compilation of appropriate algorithms in the program library;
- Creation of an Hazardous Event simulation model to run in parallel with the Baseline simulation; and
- Running sufficient iterations to capture the influence of the Hazardous Events.

From the Sensitivity Analysis of CTS 8 chlorination was identified as the most important process where the impact of a Hazardous Event should be considered. To explore the impact of a Hazardous Event the following conditions were modelled:

- Chlorination failure for 0.1, 0.5, 2, 5, 20 and 365 days.

Outside of these times Baseline conditions for CTS_8 prevailed on 365 days minus each of the failure periods.

These Baseline+Hazardous Event scenarios were simulated in parallel for sufficient iterations (50 000) to ensure that a substantial number of event iterations reflecting the shorter failure periods (0.1 or 0.5 days) were included in the total risk estimation process. The assumption of failure for 365 days was also undertaken so as to be able to place the shorter term events.

The statistics of the combined PDFs are shown in Table Error! No text of specified style in document. and demonstrate the potential impact of chlorination failure and the information gained by simulating a step series of such failure modes. Effective chlorination is clearly essential to infection minimisation despite the protection afforded by the reservoir, F/C/DAF and RSF treatment stages. Some notable features were:

- A noticeable increase in Average Risk occurred for failure duration periods as short as 0.1 days. However the risks arising from such a short event were still dominated by those associated with Baseline conditions;
- This increase was mostly noticeable in the Average Risk estimate. The median risk estimates did not change appreciably. Impact was only noticeable with the 95\(^{th}\) percentile for failure periods > 1 day; and
- For events of greater duration than 0.5 days the Average Risk exceeded the threshold value of an annualised risk probability of \( 10^{-4} \text{ person.y}^{-1} \).

This data was compared to hourly SCADA free chlorine data collected for CTS 8 immediately after chlorination and at the exit to the treatment plant after storage but before distribution. At the point of chlorination only one measurement < 0.5 mg.L\(^{-1}\) was recorded from a total of 17 000, equivalent to a total failure period of 0.04 days. This indicated that actual failure occurred less frequently than the worst simulated aggregate Hazardous Event period and the resultant increase in risk was small enough to be tolerable.
However at the storage off-take Cl₂ < 0.5 mg.L⁻¹ occurred at a rate of 13.6 days per year. This was a concern as the average annualised risk probability arising would have been of the order of 1x10⁻³ .person⁻¹.y⁻¹ compared to the Baseline of 1.7x10⁻⁵ person⁻¹.y⁻¹. How well the loss of chlorine at the plant exit reflected reduced chlorination effect in the storage tank is unclear. Yet the Hazardous Event simulation highlights the need to investigate the efficiency of disinfection in the storage tank.

<table>
<thead>
<tr>
<th>Risk Measurement</th>
<th>Statistic</th>
<th>Scenario</th>
<th>Baseline Conditions (100%)</th>
<th>Baseline (99.97%)+ vent (0.027%) (0.1 days)</th>
<th>Baseline (99.86%)+ vent (0.13%) (0.5 days)</th>
<th>Baseline (99.5%)+ vent (0.55%) (2 days)</th>
<th>Baseline (98.6%)+ vent (1.4%) (5 days)</th>
<th>Baseline (94.5%)+ vent (5.5%) (20 days)</th>
<th>Event Conditions (100%) (365 days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualized Probability (person⁻¹.y⁻¹)</td>
<td>Average 6.5x10⁻⁵</td>
<td>2.4x10⁻⁵</td>
<td>1.7x10⁻⁴</td>
<td>5.1x10⁻⁴</td>
<td>8.8x10⁻⁴</td>
<td>5.8x10⁻⁴</td>
<td>1.6x10⁻⁴</td>
<td></td>
<td></td>
</tr>
<tr>
<td>95th percentile</td>
<td>1.8x10⁻⁴</td>
<td>4.3x10⁻⁴</td>
<td>4.9x10⁻⁴</td>
<td>2.6x10⁻³</td>
<td>5.1x10⁻³</td>
<td>2.0x10⁻¹</td>
<td>9.2x10⁻¹</td>
<td></td>
<td></td>
</tr>
<tr>
<td>99th percentile</td>
<td>4.0x10⁻⁴</td>
<td>4.3x10⁻⁴</td>
<td>4.9x10⁻⁴</td>
<td>2.6x10⁻³</td>
<td>5.1x10⁻³</td>
<td>2.0x10⁻¹</td>
<td>9.2x10⁻¹</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:
Based on 50 000 iterations.
Bold entries are within one order of magnitude of the target risk, bold and underlined are more than 1 order of magnitude greater than the target risk.

### 8.4.3 Critical Limit Setting

QMRA provides a means for generating scientifically-based Critical Limits to manage control points and evaluating the appropriateness of existing ones against Benchmark risk levels. In this section we have considered how QMRA could address the setting of tolerable failure periods for chlorination in the CTS 8 treatment works.

The first manner discussed already in Section 8.3.2 is to treat infection risk probabilities as representing acceptable estimates of ‘absolute’ risk to consumers and comparing them to agreed risk ‘ Benchmarks’ e.g. infection probability of 10⁻⁴ .person⁻¹.y⁻¹ Benchmark [Hunter and Fewtrell 2001; Macler and Regli 1993]. In this instance comparison of the CTS 8 risk estimates (Table Error! No text of specified style in document.-5) indicated that the Baseline Risk was acceptable when compared to this Benchmark and this conclusion was robust as indicated by the 95th percentile (prob. infection = 6.5x10⁻⁵.person⁻¹. y⁻¹) being less than 10⁻⁴ .person⁻¹.y⁻¹ and the Tier 2 assessment yielding a similar risk estimate.

Another way is to use relative risks to identify the better indicators of ‘absolute’ risk e.g. high risk index pathogens. For example the annualised risk probability estimated for *Giardia* in CTS 8 was 8.8x10⁻¹⁰.person⁻¹.year⁻¹. This showed that *Giardia* was of much less concern than *Campylobacter* at the treatment plant exit. Hence public health protection is better served by focusing on *Campylobacter* control at CTS 8 in limit setting, monitoring and management strategies.

Another approach is indicated from consideration of the data in Table Error! No text of specified style in document.-9. It can be seen that it is possible to estimate the risks arising from varying periods of chlorination loss Hazardous Events which would cause increased...
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risks or exceed a predetermined tolerance threshold. The actual Critical Limit could be expressed in generic terms of a maximum acceptable process downtime and expressed in the following manner:

• “The chlorination failure duration period should not lead to an annualised risk > than $10^{-4}\text{ person}^{-1}\cdot\text{y}^{-1}$, or
• “The chlorination failure duration period should not lead to an annualised risk increase double the existing annualized risk”.

In the case of CTS 8 the above ‘Critical Limits’ would correspond to process failure periods of 0.5 and 0.25 days respectively (compare Table Error! No text of specified style in document.-9 and Figure Error! No text of specified style in document.-4).

A further application of the Critical Limit concept, which may be explored through modelling, is support for treatment plant upgrade planning. To illustrate using the CTS 8 example, the current modelling inputs yielded an average annualized risk probability of $1.7\times10^{-5}\text{ .person}^{-1}\cdot\text{y}^{-1}$ and the 95th percentile of $6.0\times10^{-5}\text{ .person}^{-1}\cdot\text{y}^{-1}$. An improvement target might be set such that the Baseline risk was to be decreased so as to achieve a 95th percentile risk probability for *Campylobacter* that was $1.0\times10^{-5}\text{ .person}^{-1}\cdot\text{y}^{-1}$ leading to a greater margin of treatment safety for consumers than with the current arrangements.

From consideration of the current treatment plant scheme and the CSTR relationship used to estimate disinfection, one approach might be to increase chlorination effectiveness. The first step in the planning process would be to determine how much protection would be required from this barrier i.e. the minimum (Critical Limit) barrier performance. Using @Risk Goal
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Seek different possible chlorination efficiency values were trialed. It was determined that the DEC value would need to be on average 4.75 compared to the current value of 3.88. Different design configurations could then be compared with this target in mind.

8.4.4 Bacterial Indicators and the Detection of Elevated Risk

The best known Critical Limit trigger currently used at water treatment plants is the detection of \textit{E. coli} in finished water. The question is in light of the low concentrations of pathogens required to generate significant risk, how well does bacterial indicator measurement detect significant risk of pathogen presence. It is possible to investigate this question using QMRA?

Using \textit{Goal Seek} it was estimated that given the Baseline operating conditions at CTS 8 \textit{Campylobacter} would pose an Average Annualised Risk probability of $10^{-4}$ \text{person}^{-1} \text{y}^{-1} if the source water contained 1050 \textit{Campylobacter} L^{-1}. Based on 12 dry and wet weather measurements of CTS 8 river, a median \textit{Campylobacter : E. coli} ratio of 0.021 it was in turn estimated that this level of pathogen contamination would correspond to ca 5 000 \textit{E. coli} 100mL^{-1}. The question arises as to whether a risk probability of $10^{-4}$ \text{person}^{-1} \text{y}^{-1} would be revealed by \textit{E. coli} monitoring?

Assuming \textit{E. coli} concentrations are reduced in the same manner as \textit{Campylobacter} (i.e. Tier 3 removal assumptions) it is possible to simulate the concentrations that would be seen at the treatment plant exit. Given a starting value of 5000 cfu. 100mL^{-1} the expected median concentration would be expected to be $8 \times 10^{-6}$ \textit{E. coli} L^{-1}. Even the 99.9th percentile concentration would only have been $6 \times 10^{-4}$ \textit{E. coli} L^{-1}.

Further if a Hazardous Event occurred sufficient to generate an infection risk probability of $10^{-4}$ \text{person}^{-1} \text{day}^{-1} the median \textit{E. coli} concentration encountered in the finished water would still have be ca $4.0 \times 10^{-3}$ \textit{E. coli} L^{-1} given this median ratio applied.

These simulations show clearly that in the case of \textit{Campylobacter} and CTS 8 not only was end point monitoring not timely, but the ability of \textit{E. coli} monitoring to detect elevated risk from even this very similar pathogen could be very low. The more general question arising is of what use is random end point in general. These simulation suggest that if it is to continue is should be better linked to risk assessment e.g. through challenges of treatment units.

8.4.5 Distribution System Hazardous Events

As discussed in Section 8.3.1 it is seen as more appropriate to view distribution system contamination as arising from Hazardous Events. This section illustrates two model approaches to distribution system risk analysis based on the Hazardous Event concept.

From Chapter 5 it can be seen that microbial contamination of the distribution system is commonly encountered in two different forms. Firstly it is associated with clear ingress incidents which are conceptually similar to other Hazardous Events like disinfection breakdown.

Secondly there occur sporadic positive indicator samples whose cause is never determined. As observed frequencies indicator detection are less than 1 in 1000 samples on average some could conceivably be analysis ‘false positives’. It is also well recognised however, that distribution systems have significant leakage (Australian urban figure often used is 14\% of total flow) there is clearly interconnectivity between distribution systems and their
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surroundings which could lead to ingress during transitory periods of negative pressures in pipes. Thus these sporadic positive samples must be assumed to reflect ingress even if there is some testing signal ‘noise’ from false positives unless it can be demonstrated otherwise.

Calculating the impacts of these two forms of distribution system Hazardous Event required somewhat different data analysis approaches. So we have assigned different names to the two types, ‘Acute’ meaning incident associated, and ‘Cryptic’ meaning ‘hidden’, ‘unseen’ or ‘mysteriously obscure’ for those transitory detections (single or multiple) of microbial indicators where no cause is ever identified.

8.4.5.1 Acute Distribution System Events (i.e. Incident Associated)

Based on data collected in Chapter 5 the measured probability of an incident affecting a consumer in a well maintained distribution system was 0.00154 .person⁻¹.y⁻¹ or 4.2x10⁻⁶ .person⁻¹.day⁻¹. The latter event probability value is, however, too small to simulate using @Risk and the Monte Carlo fault tree modelling (Figure Error! No text of specified style in document.-3).

This is because to sample the Hazardous Event portion of Baseline+Hazardous Event PDF as few as 10 times it would still be necessary to undertake ca 2.3 million Monte Carlo sampling iterations in total, a task not practical with current PCs running @Risk. A 100 000 iteration sampling with @Risk requires ca 2 hours and calculation speed decreases markedly as memory is exhausted. As a result full simulation of distribution system events occurring at such low frequencies needed to be undertaken using more efficient software and/or faster computer types than that selected to develop the model platform.

This limitation required us to modify our modelling strategy. Instead of considering the whole supply system we instead modelled only the worst case of those supplies impacted using the following statistics:

The likelihood of an individual within one of the impacted zones being exposed to an incident was 0.00031 d⁻¹ (4.2x10⁻⁶ .d⁻¹ / 1.5% of the total population affected);
Each incident was associated with \(E. coli\) concentrations of \(ca\) 10, 3 and 0.5 organisms.L⁻¹ on 3 consecutive days; and
Assuming sewage was the source of the contamination: the average ratio of \(E. coli\) : \(Campylobacter\) in sewage was \(ca\) 1100.

This data was used to construct a ‘worst case’ Baseline+Hazardous Event model where the water quality achieved by CTS 8 was simulated to be periodically (0.031% of iterations) subject to an increase in \(Campylobacter\) concentration of 0.01, 0.003 or 0.0005.L⁻¹. The total number of iterations used was 100 000 simulating \(ca\) 30 intrusion events. \(Campylobacter\) was seen as the most useful model as it is biologically similar to \(E. coli\) and has a high dose-response relationship.

The risk estimate statistics are shown as Event 1 in Table Error! No text of specified style in document.-10. Within the worst case zones actually affected by an acute ingress event the simulation outputs suggest that their annualized Average Risk increased by a factor of 10 and exceeded the \(10^4 .person^{-1}.y^{-1}\) Benchmark probability. If these areas were in fact especially prone to ingress this would be a concern. If, however, they were merely subject to ingress events by chance, and overall had no more chance of being affected by an ingress event than the overall population surveyed, then the increase in risk would need to take into account i.e.
that only 1.5% of the total population supplied was affected by ingress events. In this case the overall risk probability would be lower than this figure by a factor of about 60.

A quandary for water managers considering such risk estimates is whether to view the ingress affected sub-populations to be special high risk populations or whether they were simply unlucky. This question cannot be answered from the data presented here alone. The next step needed is to test the hypothesis that any high risk zones existed whose risk of ingress was significantly elevated. If such zones exist then it would be appropriate to rerun the simulation model with any revised statistics on the incidents per number of people to see if a risk requiring management existed.

**Table Error! No text of specified style in document.-10. Risk estimates for simulated distribution system events**

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Probability statistic person⁻¹.y⁻¹</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average 95th percentile Median 99th percentile</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>1.7x10⁻⁵ 6.5x10⁻⁶ 1.8x10⁻⁶ 4.8x10⁻⁴</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline+Hazardous Event 1(Acute)</td>
<td>1.7x10⁻⁴ 6.6x10⁻⁵ 1.8x10⁻⁶ 4.8x10⁻⁴</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline+Hazardous Event 2(Cryptic)</td>
<td>2.7x10⁻⁵ 6.5x10⁻⁶ 1.8x10⁻⁵ 4.3x10⁻⁴</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

8.4.5.2 *Cryptic Distribution System Events*

Modelling of Cryptic events was more straightforward. Data from Chapter 5 indicated that the rate of detection was 1 positive sample per 3000, and the concentration of *E. coli* in positive samples was ca 0.2 L⁻¹ and hence the *Campylobacter* concentrations at such times were 0.0002 L⁻¹. These indicated that a consumer would encounter water impacted by a Cryptic event with a probability of ca 0.0003.

This data was used to construct a **Hazardous Event** scenario whereby the treated water quality produced by CTS 8 was subject to an increase in *Campylobacter* concentration of 0.0002 L⁻¹ during 0.033% of simulations. The total number of iterations modeled was 100 000 simulating ca 30 iterations that included intrusion. The simulation outputs showed (Event 2. Table Error! No text of specified style in document.-10) that there was an increase in annualized risk by 70% which could be ascribed to ‘Cryptic’ intrusion. As the increase did not lead to a combined **Average Risk** probability exceeding the 10⁻⁴ .person.y⁻¹ **Benchmark**, this may be seen as tolerable. Interestingly, though the concentration of indicators was lower in the Cryptic event simulation than in the Acute events, comparison of the risk estimates suggested that Cryptic contamination is more important from a total supply system perspective.
8.5 RISKS ESTIMATES FOR OTHER CTSs AND PATHOGENS

8.5.1 Baseline Risk

Average Baseline risk estimates for CTS 1, CTS 5, CTS 6 and CTS 8 for all pathogens assessed are shown in Table Error! No text of specified style in document.-11. It can be seen clearly that the estimated risks can vary between both pathogens and CTSs by several orders of magnitude. The reasons for the large differences in the estimated risks, particularly between CTS 8 and CTS 1 on one hand, and CTS 5 and CTS 6 on the other, were apparent when the detailed inputs, system assumptions and barrier performance equivalent to those shown in Table Error! No text of specified style in document.-4 were compared.

Cryptosporidium posed the highest risk in all four systems. This result was consistent with widespread concerns regarding this pathogen and supports the belief that QMRA generates risk estimates consistent with general experience. This high risk occurred despite CTS 5 and CTS 6 having 3 and 4 barriers to pathogens respectively. The reason identified for their poor simulated performance was that the physical treatment plant removal processes (Flocculation + Sedimentation and Activated Carbon filtration) only reduced protozoa by ca 2 log10 units. The lower risks arising from water at CTS 6 were due to the additional protective effect (Median DEC = 0.88) provided by a storage reservoir located between the treatment plant intake and the river.

The differences in estimated barrier performance between CTS 6 and CTS 8 were noteworthy for related reasons. Both had river water as their primary source water. Both had a reservoir and two physical processes as their main barriers to Cryptosporidium. Further, barrier performances in both instances were estimated using local data. However the protective effect at each of these three barriers was ca 1 log10 unit greater in the case of the CTS 8 units than with CTS 6.

The generally low risk for CTS 1 was surprising in light of the concentrations of indicators in the source water (>10⁴ E. coli.L⁻¹) and the nature of the source, a major river draining urban and intensive agricultural areas. The low estimated risk was largely due to there being five treatment barriers within the treatment plant, none of which was predominant and four of which were expected to reduce Cryptosporidium. Bacteria and viruses appeared to pose little problem for CTS 1, CTS 5 and CTS 6 because of the effectiveness of the disinfection process under nominal conditions.

The poor simulated ability of CTS 5 and CTS 6 to reduce protozoan numbers generated some discussion and disagreement within the MicroRisk team. On the one hand particle size data from the actual treatment systems was used to estimate the 2 log10 reduction credit. However the survey of Hijnen et al. [2005] suggested that 3 to 4 log₁₀ reduction might have been expected.

This discussion again highlighted how risk estimates can vary significantly according to the choice of input assumptions, the need to develop agreement among CTS stakeholders on the assumptions to be used in any given risk estimation exercise and the uncertainties which may be disguised numerical process data. In the case of CTS 5 and CTS 6 this was a particularly
Table Error! No text of specified style in document.-11. Comparison of Baseline Risk Estimates Calculated for 4 CTSs

<table>
<thead>
<tr>
<th>Measure</th>
<th>CTS</th>
<th>Pathogen</th>
<th>Crypto-</th>
<th>Giardia</th>
<th>Campylobacter</th>
<th>E. coli O157</th>
<th>Norovirus</th>
<th>Enterovirus</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>spordi</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>um</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annualised</td>
<td>CTS 8</td>
<td>1.4x10^{-5}</td>
<td>1.8x10^{-10}</td>
<td>1.7x10^{-5}</td>
<td>-^2</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Probability</td>
<td>CTS 1</td>
<td>7.7x10^{-6}</td>
<td>4.7x10^{-11}</td>
<td>3.7x10^{-11}</td>
<td>6.5x10^{-13}</td>
<td>-</td>
<td>-</td>
<td>5.3x10^{-11}</td>
</tr>
<tr>
<td>of infection.</td>
<td>CTS 5</td>
<td>9.0x10^{-2}</td>
<td>2.9x10^{-5}</td>
<td>1.7x10^{-5}</td>
<td>-</td>
<td>(5.8x10^{-4})</td>
<td>(7.8x10^{-5})</td>
<td></td>
</tr>
<tr>
<td>person^{-1}.</td>
<td>CTS 6</td>
<td>1.3x10^{-3}</td>
<td>2.8x10^{-5}</td>
<td>2.5x10^{-5}</td>
<td>-</td>
<td>(1.7x10^{-5})</td>
<td>(2.2x10^{-6})</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
The risk estimates in brackets are based on upper 95th percentile uncertainty and are derived from upper limit inputs rather than typical source water concentrations.

*E. coli* O157 and O111 biotypes were both tested for but not detected in 20 composited cow faeces samples from within the catchment. Other Shiga toxin producing *E. coli* were detected but their significance is uncertain.

difficult one to resolve. The choice was between literature data based on microbial removal and high quality local particle sizing data. Because the particle size data were conservative and local (and therefore nominally of a higher Tier based on the classification applied here) they were used to generate the data in Table Error! No text of specified style in document.-11. One safe conclusion is that there is an urgent need for more data on factors controlling the removal of microorganisms at the physical barriers at CTS 5 and CTS 6. The best way to gain such removal data is probably to experimentally using microbial tracers to isolated treatment subunits isolated.

### 8.5.2 Sensitivity Analysis

In Section 8.2.6.2 a full system Sensitivity Analysis is illustrated. In the latter instance the main aim of the analysis was to identify the most important barriers to pathogens in CTS 8. There are other potential uses of Sensitivity Analysis, three of which are illustrated in Table Error! No text of specified style in document.-12.

Table Error! No text of specified style in document.-12. Further examples of the value Sensitivity Analysis

<table>
<thead>
<tr>
<th>CTS</th>
<th>Stage / Barrier ; Pathogen Considered</th>
<th>Management Issue</th>
<th>Baseline Assumption</th>
<th>Sensitivity Test Value</th>
<th>Average Baseline Annualised Risk .person^{-1}.y^{-1}</th>
<th>Annualised Risk with Test Value(s) .person^{-1}.y^{-1}</th>
<th>FS</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTS_1</td>
<td>River Source Water; <em>E. coli</em> O157</td>
<td>Concentrations measured are much less than normally expected for river water. How much of a problem would poor analysis recovery pose for risk estimates. Ozonation, often seen as a major</td>
<td>Average is 0.081 organisms .L^{-1}. Fifth and 95th percentiles are 0.06 and 0.1 respectively</td>
<td>4000 organisms .L^{-1} reported in Chapter 5.</td>
<td>5.0x10^{-14}</td>
<td>2.2x10^{-4}</td>
<td>4.7</td>
</tr>
<tr>
<td>CTS_1</td>
<td>Ozonation Treatments;</td>
<td>Pre-ozonation and Ozonation</td>
<td>No ozonation</td>
<td>1.7x10^{-5}</td>
<td>7.2x10^{-5}</td>
<td>0.62</td>
<td></td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Cryptosporidium barrier for protozoa may need to be stopped when Bromide concentrations lead to unacceptable bromate formation</th>
<th>reduces Cryptosporidium by on average 0.33 and 0.4 log(_{10}) units</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTS_5 Extraction of River Water; Norovirus</td>
<td>CTS extracts river water when there is low pollution i.e. closed intake during Hazardous Events. How sensitive is viral risk to this policy.</td>
</tr>
</tbody>
</table>

In Chapter 3 (source water chapter) one striking difference was between the concentration of *E. coli* O157 reported and that considered to occur typically in river sources. The reason for this discrepancy was not clear but it could have been due to analytical problems or real differences in the quality of the river water. One question arising was how urgently this issue needed resolving. Sensitivity Analysis using the potential concentration value of 4 000 *E. coli* O157 (Chapter 3) showed that while the potential discrepancy was very high (FS=4.7), the maximum annualized risk to consumers under Baseline simulations conditions was still well below a Benchmark probability value of 10\(^{-4}\)person\(^{-1}\).y\(^{-1}\).

A second issue at CTS 1 was the potential for increased risk arising if ozonation was shut down. Ozonation at the treatment plant was used routinely to oxidise organic matter with disinfection of protozoa was seen as a opporune secondary benefit. However there was potential for the two ozonation barriers to be disabled in the event of excessive Bromate formation leading to reduced removal of *Cryptosporidium*. Sensitivity Analysis showed that because of the effect of other barriers, the impact on risk even over 1 year would be marginal.

The third case considered was a policy of selective extraction employed at CTS 8. Sensitivity Analysis indicated the policy had a major protective effect.

**8.5.3 Hazardous Events & Critical Limits**

The range of Hazardous Events which may impact on any given CTS is very large. So it was not practical to do an exhaustive set of simulations. Nonetheless a number of additional events were identified in discussions with local CTS stakeholders, from SCADA data and from Chapters 3-6. Of these five were selected for simulation to assess the diversity of information that could be gleaned by Hazardous Event analysis (Table Error! No text of specified style in document.-13).

In the case of the CTS 1 the local managers were concerned about the prospect of a motorway fuel spill and its potential impact on the treatment plant. It was speculated that even small quantities could foul major filters (Rapid Sand Filter and GAC) and reactors (Ozone contact tanks) and necessitate cleaning. This led us to simulate a clean-up period of 7 days during which protection was provided by chlorination and hence the system was
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vulnerable to *Cryptosporidium* contamination because of its resistance to chlorine. It can be seen that the annualised risk rises by a factor of 1 000 and the estimated probability of illness is much higher than $10^{-4}\cdot \text{person}^{-1}\cdot \text{y}^{-1}$. Further, even if the repair period could be reduced to 1-2 days the additional risk would still be great and hence other action such as a boiled water alert on top of chlorination would need to be considered.

Sensitivity Analysis of CTS 5 performance highlighted water quality sensitivity to intake gate operation. Hazardous Event scenario analysis provided further information. Were no gate management in place average annualized risk would have been at least 19 times higher. The impact of a delay in closing the intake was also substantial. This highlighted the need for timely warning of event onset where source extraction is being managed.

CTS 6 included extensive diary and SCADA data detailing barrier performance (next section). This information allowed among other assessments determination of whether chlorination failure was occurring at tolerable rates. Analysis of the in line chlorine monitoring data indicated that at worst chlorine dosing failed for a total time of 1.5 hours over a 12 month period. The impact of simulated worst case failure on *Campylobacter* showed a detectable but only small increase in the Annualized Risk probability compared to the $10^{-4}\cdot \text{person}^{-1}\cdot \text{y}^{-1}$ threshold.

The final Event scenario considered was that of multiple concurrent Events. A concern for CTS 8 and CTS 6 type systems which draw their supply from a reservoir is that during high run-off events there can be concurrent polluted input and short-circuiting [Hipsey et al. 2005]. Further, storms frequently cause power failures which could affect treatment plant equipment such as dosing pumps. Two scenarios were considered with these three Events in mind. Concurrent contamination of run-off and short circuiting were estimated to double the Annualized Risk probability for *Campylobacter* to $3.4\times10^{-5}\cdot \text{person}^{-1}\cdot \text{y}^{-1}$. When combined with a short duration power failure leading to chlorination loss during a storm event they could increase annualized risk 11 fold in a short time, confirming the need for avoiding or actively managing periods of concurrent Hazardous Events.

Table Error! No text of specified style in document.-13. Illustrative Hazardous Event Impacts on Risk

<table>
<thead>
<tr>
<th>CTS</th>
<th>Pathogen: Stages/Barriers Altered</th>
<th>Simulated Event (= Variations from Baseline)</th>
<th>Total Duration of Event Condition(s)</th>
<th>Average Baseline Risk (Annualized)</th>
<th>Baseline + Hazardous Event Risk (Annualized)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTS_1</td>
<td><em>Cryptosporidium</em> / Loss of major barriers</td>
<td>Loss of physical barriers due petroleum spill necessitating clean-up. Only remaining treatment is chlorination.</td>
<td>7 days</td>
<td>$1.4\times10^{-3}$</td>
<td>$1.7\times10^{-4}$</td>
</tr>
<tr>
<td>CTS_5</td>
<td><em>Norovirus</em>/ Evaluation of intake operation</td>
<td>No gate operation leading to exposure to periodic Hazardous Events Delay in intake gate closure of 4 h for each of 29 Events per year due to time needed for rapid assay incubation</td>
<td>57 days</td>
<td>$&lt;5.8\times10^{-4}$</td>
<td>$2.7\times10^{-2}$</td>
</tr>
<tr>
<td>CTS_6</td>
<td><em>Campylobacter</em>/ Loss of disinfection capacity <em>Campylobacter</em></td>
<td>Total suboptimal chlorination periods based on analysis of SCADA data – worst case of total loss of disinfection assumed</td>
<td>4.75 days</td>
<td>$3.4\times10^{-3}$</td>
<td>$3.4\times10^{-3}$</td>
</tr>
<tr>
<td>CTS_8</td>
<td><em>Campylobacter</em></td>
<td>Short circuiting leads to reservoir</td>
<td>1.5 hours</td>
<td>$2.5\times10^{-6}$</td>
<td>$3.2\times10^{-6}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>9 days</td>
<td>$1.7\times10^{-5}$</td>
<td>$3.4\times10^{-5}$</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>CTS</th>
<th>Pathogen: Stages/Barriers Altered</th>
<th>Simulated Event (= Variations from Baseline)</th>
<th>Total Duration of Event Condition(s)</th>
<th>Average Baseline Risk (Annualized) person(^{-1}) y(^{-1})</th>
<th>Baseline Hazardous Event Risk (Annualized)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impact of concurrent catchment and treatment plant events</td>
<td>creating protection factor of 10 for 24 hours through dilution (i.e. DEC = 1). Nine short circuiting events occur per year. Short circuiting leads to reservoir creating protection factor of 10 for 24 hours through dilution (i.e. DEC = 1). Nine short circuiting events occur per year. During this period chlorination loss occurs due to power failure for 2.4 hours (0.1 days).</td>
<td>0.1 days</td>
<td>1.8x10(^{-4})</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The risk estimates in brackets are based on upper 95th percentile uncertainty and are derived from upper limit inputs rather than typical source water concentrations.

The value of the Event analyses illustrated lies not only in the actual estimates presented. They also demonstrate how QMRA can simulate Events and other hazardous scenarios to produce risk estimates useful for management and development of Critical Limits. In the case of CTS 1 it was clear that plant shut down even for a short periods posed high risks because of the contamination levels in the source water. Selective water intake at CTS 5 is a beneficial management activity. However risk was not reduced below the 10\(^{-4}\) probability threshold so additional management should be investigated e.g. to reduce the response period before intake closure. At CTS 6 chlorine dosing was shown to be maintained at a level sufficient to reduce risks arising from plant failure. The CTS 8 analysis showed that Baseline operating conditions provide sufficient barrier protection to mitigate two concurrent environmental risks. But three concurrent events pose a significant threat.

8.5.4 SCADA Data Analysis

To ensure that water treatment processes work properly many Water Treatment Plants are monitored in real time by online control and monitoring systems, that is Supervisory Control and Data Acquisition (SCADA) systems. On a regular basis these systems collect parameters such as flow, turbidity, pH, disinfectant residuals and temperature. Although these measures of process performance cannot be directly translated into pathogen removal, they still provide a valuable source of (event frequency/duration) information for undertaking assessments of risks. Concurrent with the analysis in this Chapter analysis of one such system was undertaken [Nilsson 2006]. This section presents the key findings of this work.

The overall objective of Nilsson’s [2006] MSc project was to identify, compile, and critically evaluate the use of SCADA data sets in QMRA and the implications of its use for risk management. By analysing diary records and deviation reports in parallel with SCADA data sets, advantages and limitations to SCADA in its ability to identify frequencies, durations and magnitude of events were assessed. Ten-minute mean values for the time period 01/Oct/2004 to 19/Sep/2005 were collated for CST 6 for the following analytes judged relevant to pathogen risk assessment:

1. Turbidity in raw water, filtrate water and drinking water.
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2. Chlorine residual in raw water weir and in drinking water.
3. pH in flocculation chamber one.

Interpretation of this data raised three critical challenges:

1. The task of managing and analysing in a PC environment data sets amounting to gigabytes;
2. How to recognise Events in a timeseries record – known as the ‘Change Point’ problem. (There is no single statistical technique available for addressing this and simple visual inspection is arguably as effective as many approaches as a first step).
3. Linking timeseries data to actual plant operation.

All three issues were sufficiently overcome to generate useful system performance statistics. Using a combination of visual assessment of the SCADA record and CUSUM analysis [Taylor, 2000] a total 119 candidate ‘events’ were provisionally identified. Seventy one percent were assessed as being non-hazardous whereas the other 29 % were considered being possibly hazardous based on their general characteristics and examination of concurrent treatment plant diary records. Of those considered non-hazardous, 85 % were the result of maintenance and 15 % the result of incidents. Of those considered possibly hazardous, 76 % were of unknown cause and 24 % were caused by maintenance or incidents.

The most immediate use of the timeseries data was to estimate the frequency and duration of treatment failure. Estimation of impact magnitude was more problematic but for modelling purposes total process failure could be used to assess the worst case and hence the need for further work.

The duration of most identified events ranged between 0.5 and 2.3 hours. The CUSUM was most useful for the detection of longer term trends in timeseries which were thought likely to result from early summer algae blooms (Figure Error! No text of specified style in document.) or adjustment of dosing levels (pH, Cl₂). SCADA analysis was used as the basis for estimating Hazardous Event duration in regard to disinfection (e.g. CTS 6 and CTS 8, Table Error! No text of specified style in document.).
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8.6 DISCUSSION

8.6.1 Uses and Limitations of QMRA Risk Estimates

From the CTS simulation outputs it appears that QMRA has reached the point where it can be operationally used by water utilities to produce a range of risk estimate based products which can be used to inform pathogen management. In this success and the ease with which it is possible to generate risk estimates though also lies the temptation to misuse. This section outlines the strengths and limitations of full CTS QMRA undertaken here to alert users of the need to balance its strengths and limitations.

8.6.1.1 QMRA Limitations

QMRA models and simulations are not reality but idealisations. Thus the input PDFs (source water and barriers) and output infection rates should never be seen as final fixed representations of water quality but rather best approximations which need ongoing revision and care in use and which will always have a level of associated uncertainty and variability. Accordingly newcomers to QMRA should view output risk estimates not as absolute guides to water management to be used in isolation but rather as information to be interpreted in light of other best practice management principles. Consideration of data variability and uncertainty should be routine. Tier assessment is one possible aid for identifying the best possible inputs and highlighting uncertainties. But there will often be multiple choices available which can yield markedly different risk estimates as was encountered with CTS 5 and CTS 6.

A related need is to recognise the principle “the whole is not necessarily the sum of the parts” which in a sophisticated way QMRA simulations tacitly imply. At present QMRA is well suited to linear risk calculations and as good data is available for most barriers credible modelling is possible. However the PDFs do not as yet account all sources of variance and simple proportional decimal reductions are an empirical approximation. Current algorithms do not recognise that pathogens may exist as a number of subpopulations with differing values, such as resistance to disinfection. Simple DECs do not account for contaminant antagonisms which can affect removal. It is unclear how colloids in different waters might block pathogen binding sites in flocs and on filter media [Song et al. 2005]. The issue of hydraulic flow complicates the estimation of disinfection and probably the effectiveness of other processes effectiveness. Finally uncertainty arises from translating laboratory data or surrogate data to the behaviour of pathogens in full-scale systems.

8.6.1.2 QMRA Benefits and Strengths

While recognizing these limitations the strengths and potential of QMRA simulations undertaken here are also clear. For all its limitations QMRA still appears to provide the most credible quantitative synthesis of currently available data and knowledge on water treatment and risks. So its introduction into widespread use seems reasonable provided the opportunities for misuse are avoided and revision of assessments is routine.

The recognition that for any given barrier there are alternative credible filtration, coagulation and disinfection removal models highlights implicitly the uncertainties in current knowledge
exists and posits hypothetical pathogen removal barrier effects which may be tested on a CTS. Water treatment is generally analysed on a barrier by barrier basis. QMRA makes possible a start on quantitative analysis of complete systems.

Easily conceived endpoint risk measurements (annualised infection rates, DALYs, Chapter 2) which address the primary concern of minimising risks to human health provide clear targets for setting Critical Limits for upstream barriers or a CTS as a whole and management action triggers. This contrasts with older coliform-based targets which did not have as clear a quantitative relationship to risk levels.

Preliminary desktop simulations form are an aid conceiving understanding water treatment systems as they forces the water manager to define the system and the way it is believed to function, its effectiveness in light of available knowledge and their current assumptions about it. The same process exposes knowledge gaps. By simple modification of models it is possible to explore the impacts of Events and prioritise them. Further it is possible to assess the impact of past, potential single and multiple Hazardous Events. It allows Hazardous Events to be differentiated from non-Hazardous Events based on their impact on infection rates.

8.6.1.3 Technology Use Principles

A feature of the above benefits of QMRA is that they arise from QMRA functioning as tool for better understanding the structure and function of CTSs. Like all tools, QMRA has its limits and needs a guide to appropriate use. Based on experience gained during the MicroRisk project the following application principles and approaches are proposed to promote balanced use:

1. QMRA is well adapted for use as an hypothesis testing and generating tool and should be used in this fashion;
2. The existence of competing alternate input data makes possible a broader sensitivity testing. This should be undertaken where ever warranted;
3. WHO [2003] recreational water guidelines propose a hybrid matrix for assessing microbiological risks which combines both qualitative and quantitative criteria. This model could be adapted for QMRA use where pathogen management decisions are based on other criteria as well as QMRA assessments;
4. Lack of transparency can be a frustrating feature of computer model outputs. QMRA input and output data should be well documented and transparent to aid auditing and revision;
5. Reports on water quality and barrier effectiveness should routinely include estimates of variability and uncertainty;
6. Primary data should be managed so as to promote sharing and reanalysis;
7. Protocols should be developed for periodically reviewing CTS QMRAs in light of new knowledge; and
8. Reports should be divided into two distinct sections with:
   a. The first part providing a basic interpretation of risk estimates in terms of Benchmarks, guidelines, Critical Limits, Tolerable Risks and action levels;
   b. The second part identifying caveats to the basic interpretation.

8.6.2 Water Safety Plans, Hypothesis Falsification and QMRA
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Water Safety Plan [WHO, 2004] implementation as currently promoted is focused on Qualitative Risk Assessment or a screening level risk assessment. At the heart of this process is the risk assessment matrix where qualitative risk scores are assigned to hazards and Hazardous Events based on expert perception of risk severity and likelihood. This process of risk estimation and assignment is in effect an application of the first stage of scientific methodology i.e. generating hypotheses about risks based on current water science paradigms and expert opinion. That hypotheses generated in the process of developing WSPs should then be tested is also clearly supported in WSP guidelines. In addition to the emphasis on the use of statistics, there is in the HACCP process summary a clear proposal to undertake robust hypothesis testing as well i.e. “validate and verify management”, “produce and verify flow charts”, “test management actions”.

The difficulty with Qualitative Risk Assessment scores is that they are not well suited to robust statistical testing. Some non-parametric testing of the scores of each risk may in theory be undertaken but Qualitative Risk Assessment scores are necessarily very value judgment based because the scores are really numerical equivalents of “good, fair, etc. A second limitation is that while Qualitative Risk Assessment assessments can easily evaluate single hazards, how to assess the impact of concurrent multiple risks is less clear. The problem of how to consistently amalgamate qualitative assessment scores is a common problem in State of the Environment reporting. One approach is to introduce weightings. But these again are prone to value judgment bias.

Alternatively QMRA can be used to provide a measure of risk frequency and severity which is conceptually the same as that generated by the qualitative matrix system (Figure Error! No text of specified style in document.-6). Quantitative Microbial Risk Assessment appears to support the need for risk hypothesis falsification in a range of ways:

1. The process of infection risk calculation yields product numbers which directly incorporate scientific quantitative data on a CTS;
2. The infection risk rate calculation yields in effect a Hazardous Event likelihood X severity measurement (Figure Error! No text of specified style in document.-6);
3. There is no need to introduce ad-hoc weightings to account for the relative importance of different barriers, as infection rate calculation takes the magnitude and effect of different barriers into account automatically;
4. QMRA could in theory be used to test/verify Qualitative Risk Assessment derived hypotheses;
5. The use of QMRA necessitates the framing of risks identified by Qualitative Risk Assessment in as precise a mathematical format as possible with available data;
6. The selection of input data on source water pathogen levels and barrier effectiveness for new systems in effect posits hypotheses about source water pathogen concentrations and the effectiveness of barriers which can be tested experimentally;
7. Qualitative Risk Assessment has difficulty generating whole of system risk assessments which balance the significance of the different steps. QMRA fills this gap;
8. Events of the same class (e.g. high run-off) will inevitably vary in magnitude. QMRA provides a means of quantifying the impact of magnitude differences;
9. Using the data and system definition developed through QMRA can be used to explore the impact of possible rare and multiple barrier failure scenarios to see if they deserve further qualitative risk assessment or other study; and
10. The concept of Tolerable Risk defined in terms of risk of infection or equivalent appears to address the need for a consistent approach to defining Critical Limits.
The MicroRisk data and project itself also appears to provide significant assistance to WSP method development. This is because the project has generated a large range of data on CTSs which can be used for those which have not been previously the subject of risk assessment in part or whole for first cut simulations.

\[
\text{Severity} = n_1 \\
\text{Likelihood} = n_2 \\
\text{Matrix Product Score} = n_1 \times n_2
\]

Figure Error! No text of specified style in document. The equivalence of QMRA and Qualitative Risk Assessment Processes

8.7 CONCLUSIONS - HOW TO USE QMRA

QMRA does not replace Qualitative Risk Assessment and Water Safety planning but appears to greatly support these developments. In particular:
1. Risk estimation appears capable of replacing the less reliable numerical scoring used in qualitative risk assessment matrix completion;
2. QMRA appears to provide a means of assessing whether the treatment system as a whole is vulnerable to malfunction or failure and which individual components are most vulnerable/critical/suboptimal; and
3. QMRA can provide a rational basis for setting numerical Critical Limit targets.

Despite the inherent variability and uncertainty of input PDF and output statistics from risk simulations, QMRA methodology appears capable of providing a range of objective numerical assessments of system performance as well as uncertainty in such performance measures which can be used to improve existing water treatment management and evaluate the need for upgraded or new source water management or water treatment. Uses for such information include: the setting of management targets, triggering of actions such as boiled water directives, identifying research priorities and estimating the effect of rare, high impact events. The following is a check list advice notes which tries to capture the messages above in simplified form:
1. Use QMRA as a tool to ask Questions and Test Hypotheses in the context of a larger Water Safety Plan.
2. Define clearly in mathematical form the barriers and inputs including surface waters and reservoirs.
3. Define first a Baseline, nominal or reference conditions noting any Hazardous Events which may be included inadvertently (e.g. periodic high run-off; seasonal variation).
4. For conceptual and actual Hazardous Events quantify not only their size but also their frequency and duration.
5. When interpreting outputs give equal weight to uncertainty and variability as is given to modal data.
6. When generating PDFs recognize the existence of a range of sophisticated mathematical tools and programs which will yield the best functions possible. Don’t hesitate to work with a biometrician.
7. Water Safety Plans are likely to be developed by committees. Given the possible permutations and combinations in simulation inputs, (healthy) disagreement is likely and a practical way forward is needed. The following scheme is proposed for use when and after a set of primary simulation models are developed which involve periodic revision and gap identification:
   a. Initially select a set of provisional input data as the starting Baseline;
   b. Calculate provisional Baseline (or parts thereof) risks and circulate them for review and feedback (the inputs and outputs in this document) is subject to review;
   c. Refine the provisional assessment to generate the first consensus Baseline CTS risk model for a CTS/pathogen and risk estimates;
   d. Subject the management framework to periodic review; and alter/Refine as necessary (post MicroRisk use of simulation products);
   e. Generate risk estimates associated with derivative simulation products such as priority Events, and barriers. Critical Limit setting should be similarly subject to provisional development, review and modification as necessary; and
   f. Repeat the review process as needed e.g. in response to changes in general scientific knowledge, a local CTS review or experimental work which leads to Baseline modification.
8. In line with recreation risk guidelines it is proposed that the concept of provisional assessments be used where appropriate e.g. where a consultant develops a first cut plan for review and refinement prior to being adopted as v. 1.0 consensus model. Such a scheme would be aided by having a simulation process which is flexible, straightforward to do and interpret and hopefully simple enough to interactively explore the numerous scenario in local manager workshops. Transparency in input assumptions is likely to be essential.
9. Recognize that Hazardous Events include not only short duration shocks to CTS functioning but may be chronic such as poorly defined long term infiltration of water or cyclic such as seasonal contamination of source water from snow melt.
10. Establish a generally acceptable quantitative measure of risk (e.g. 1 infection per 10,000 population per pathogen per year at a 95% confidence level).
11. Use QMRA to answer four basic questions about a water supply system in respect to each pathogen with a view to risk minimization.
   a. Is the nominal/Baseline risk tolerable? (Baseline Scenario simulation). If yes how much safety margin is there? If no how much additional?
   b. Which barriers and sources of variability in the process appear to be most critical to maintain (Sensitivity simulation)?
   c. What is the potential impact of a hazard (at a control point)? What is the potential impact of concurrent Hazardous Events?
   d. What (Critical) Limits need to be aimed for / maintained overall and individually?
12. In respect to Critical Limits some critical questions are:
   a. What performance has to be maintained v. How much short of my desired target am I?
b. What safety factors should be applied to Hazardous Events compared to the tolerable Baseline risk?
c. How close to the 95th percentile limit is acceptable given uncertainty and Hazardous Events?

8.8 REFERENCES


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Signor, R.S., Ashbolt, N.J. and Roser, D.J. (2005) Quantitative Microbial Risk Assessment and management implications of rainfall induced runoff entering a source drinking-water reservoir Submitted to Journal of Water Supply: Research & Technology AQUA.


## APPENDIX 1. DATA AUDIT SCORING KEY

<table>
<thead>
<tr>
<th>Simulation Stage Class</th>
<th>Audit Score = 1</th>
<th>Audit Score = 2</th>
<th>Audit Score = 3</th>
<th>Comments on each Stage Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Source water concentration</td>
<td>Point estimate of pathogen input/source water concentration based on: local indicator data &amp; generic ratios of indicators: pathogens for land use or PDF of pathogens from similar source water type.</td>
<td>Source water pathogen PDF estimate based on local indicator data and local pathogen:indicator ratio data or Basic pathogen PDF (e.g. triangular or uniform) based on local summary statistics data.</td>
<td>System specific pathogen PDF estimate with uncertainty and/or recovery estimates.</td>
<td>For maximum precision this should be the concentration at the entrance to the water treatment plant.</td>
</tr>
<tr>
<td>2. Reduction by pre WTP processes and WTP Physical/chemical processes not designed explicitly for disinfection (e.g. reservoir sedimentation, riverbank filtration)</td>
<td>Generic literature reduction for treatment process with credible effectiveness range such that a simple PDF (e.g. uniform or triangular) can be constructed or Reduction variability based on removal algorithm function which can be used with good specific point removal estimates for the treatment system.</td>
<td>High quality pathogen removal estimation PDF function based on: Local, credible, relevant surrogate data (particle size removal for the appropriate size band) or PDF based on compilation/collation of data for closely comparable systems [e.g. relevant subset of Hijnen et al. 2005]</td>
<td>Very high quality reduction PDF function based on: Local measurements of microbial removal using indicator microorganisms in actual system or pilot plant results or Surrogate PDFs calibrated with microbial removal such that the relationship between particle and pathogen removal is credible.</td>
<td>Includes organic oxidation processes which might have some impact on microbial concentrations but are not optimised for this purpose. Can include reservoir and off bank filtration.</td>
</tr>
<tr>
<td>3. Disinfection</td>
<td>Disinfection reduction estimate in the form of a simple PDF based on credible relevant data such as disinfection PDF for a similar water treatment plant disinfection: or Disinfection based on USEPA CT methodology.</td>
<td>Reduction PDF that accounts for local disinfection system design and incorporates the following: Hydraulics based empirical CSTR assumption Temperature variation Disinfectant concentration as measured/expressed as a simple PDF or point value based on dosing rates. Pathogen group response (k value).</td>
<td>Optimal PDF that accurately accounts for all local variables including: Hydraulics (detention time and extent of mixing) Temperature variation Disinfectant concentration, availability and decomposition rate Specific pathogen response. Reliability of disinfection measurements. Variability in the coefficients. Correlation between these variables.</td>
<td>Disinfection separated from other process. Criteria need to be expanded to include ultraviolet radiation systems.</td>
</tr>
<tr>
<td>4. Distribution</td>
<td>See below</td>
<td>See below</td>
<td>See below</td>
<td>Not included currently in</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Simulation Stage Class</th>
<th>Audit Score = 1</th>
<th>Audit Score = 2</th>
<th>Audit Score = 3</th>
<th>Comments on each Stage Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>5. Consumption</td>
<td>General water consumption PDF – proposed one is conservative Melbourne Australia data</td>
<td>Country specific water consumption PDF</td>
<td>Subpopulation specific water consumption (age-group, city, region, sensitive subpopulation)</td>
<td>Baseline model Consumption PDFs appear to have the least variation of any stage.</td>
</tr>
<tr>
<td>6. Infectivity</td>
<td>Dose response curve for generic bacteria, virus or protozoa similar to the organism of interest</td>
<td>Dose response curve for same bacteria, virus or protozoa as the organism of interest</td>
<td>Dose response curve for the same bacteria, virus or protozoa as the organism of interest and: The same exposed population or Uncertainty/variability estimates for the curve’s coefficients</td>
<td>Care needs to be taken in using some distributions to calculate infection rates where the consumption is notionally &lt; 1 organism per person Not included currently in model. Included for consideration</td>
</tr>
<tr>
<td>7. Total Disease Burden</td>
<td>DALY for generic bacteria, virus or protozoa similar to the organism of interest</td>
<td>DALY for same bacteria, virus or protozoa as the organism of interest.</td>
<td>DALY for same bacteria, virus or protozoa as the organism of interest and population of concern.</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
This Audit Score assignment table is applicable only for a Baseline assessment. A system also needs to be developed also for Hazardous Events which balance the extent of the data available with the need to model extreme events for which only limited data if any is available.

Audit Score assignment for distribution systems needs to be added. It has been omitted for the moment as the assessment is for Baseline conditions where quality at the point of exit from the treatment works should be drinkable.
In assigning a rating, a score intermediate between the different optimal classes may be assigned – e.g. 2.5 for disinfection where the local temperature and disinfectant decomposition are known but where hydraulics is not well characterised. Because of the range of numerical inputs into disinfection effectiveness estimation and the varying degrees with which the mid point variability and uncertainty of this data can because of known would particularly need as expert assessment of where a system lay between the Audit Score 2 and 3 criteria.
Overall score is estimated as arithmetic mean +- standard deviation for the combined scores for all significant transformation stages.
Weighting might be considered for some stages e.g. to provide greater emphasis on the quality of the disinfection analysis because of its importance or less on consumption because the variability in consumption is much less than the other stages.